Consumer Attitude Metrics For Guiding Marketing Mix Decisions

Dominique M. Hanssens[1], Koen H. Pauwels[2], Shuba Srinivasan,[3]
Marc Vanhuele[4] and Gokhan Yildirim[5]

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[1] Bud Knapp Professor of Marketing, UCLA Anderson School of Management, Los Angeles, CA 90095-1481, Phone: +1 310 825 4497, E-mail: dominique.hanssens@anderson.ucla.edu.

[2] Professor of Marketing, Özyeğin University, Istanbul, 34794 Turkey, Phone + 216 5649532, E-mail: koen.pauwels@ozyegin.edu.tr.

[3] Associate Professor of Marketing and Dean's Research Fellow, Boston University School of Management, Boston, MA 02215, Phone: (617) 353-5978, E-mail: ssrini@bu.edu.

[4] Associate Professor of Marketing, HEC Paris, 78351 Jouy-en-Josas, France, Phone: +33 1 39 67 94 42, E-mail: vanhuele@hec.fr.

[5] Assistant Professor of Marketing, Lancaster University, Management School, Department of Management Science, Bailrigg, Lancaster, LA1 4YX, UK, Phone: (+44) (0)1524 5-93876, E-mail: g.yildirim@lancaster.ac.uk.

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Abstract

Marketing managers often use consumer attitude metrics such as awareness, consideration, and preference as performance indicators because they represent their brand's health and are readily connected to marketing activity. However, this does not mean that financially focused executives know how such metrics translate into sales performance, which would allow them to make beneficial marketing mix decisions. We propose four criteria – potential, responsiveness, stickiness and sales conversion – that determine the connection between marketing actions, attitudinal metrics, and sales outcomes.

We test our approach with a rich dataset of four-weekly marketing actions, attitude metrics, and sales for several consumer brands in four categories over a seven-year period. The results quantify how marketing actions affect sales performance through their differential impact on attitudinal metrics, as captured by our proposed criteria. We find that marketing-attitude and attitude-sales relationships are predominantly stable over time, but differ substantially across brands and across product categories with different levels of involvement. We also establish that combining marketing and attitudinal metrics improves the prediction of brand sales performance, often substantially so. Based on these insights, we provide specific recommendations on improving the marketing mix for different brands, and we validate them in a hold-out sample. For managers and researchers alike, our criteria offer a verifiable explanation for differences in marketing elasticities and an actionable connection between marketing and financial performance metrics.

Introduction

Brand managers are urged to compete for the ‘hearts and minds’ of consumers and often collect *brand health* indicators such as awareness, liking, and consideration to this end. These indicators help understand the state of mind of consumers and how marketing affects it. More bottom-line oriented managers, in contrast, typically assess marketing effectiveness at the observable transaction level, with measures such as “advertising elasticity” and “return on sales.” This practice may satisfy managers focused on financial returns (including the CFO), but it leaves the deeper reasons for marketing success or failure unexplored. Inasfar as these reasons change, past sales impact of marketing may not be the best predictor of its future sales impact.

In theory, brand health indicators are predictive of later marketing and bottom-line performance, but this connection is poorly understood. In addition, marketers currently have little guidance on how a better understanding of this connection can be translated into improved decisions on the marketing mix. How actionable is it, for instance, to know that brand consideration stands at 70% while brand liking stands at 40%? Conventional wisdom (e.g. Kotler and Keller 2012) 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 consideration may still be possible. In addition, consideration 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 consideration could be longer-lasting. As to the end result, consideration gains may convert into sales at a higher or lower rate than liking gains do. To complicate matters, marketing-attitude and attitude-sales relationships may be generic to the category, or specific to the brand, indicating competitive (dis)advantage. Finally, these relationships could change over time, obscuring their value and necessitating their dynamic evaluation to guide future marketing mix allocations.

In sum, it is no small task for brand and marketing managers alike to use consumer attitude information to guide their marketing strategies and actions. Yet such guidance is important because managers are charged to allocate marketing resources that provide *noticeable* and *long-lasting* improvements in their brands' business performance. Our objective is therefore to provide concrete directions on how the effectiveness of marketing mix actions, and therefore also the allocation of resources, can be improved by examining attitude metrics. More specifically, we propose criteria on these metrics that identify conditions under which they should be targets of marketing action. For example, when and how should a brand focus on increasing brand consideration versus brand liking? By applying these criteria managers with access to the relevant information on the costs of each marketing instrument can determine the respective investment appeal of each of these instruments.

We proceed in three steps. We start by proposing a conceptual model that sets up and examines the criteria by which marketing actions impact consumer attitude metrics and their conversion into sales. We then validate our approach empirically on brands from four consumer product categories and demonstrate that a better understanding of the connection between marketing actions, consumer attitudes, and sales leads to better sales forecasts. Third, we demonstrate how our approach offers important guidance for marketing spending decisions.

Although this research topic is at the core of the study of marketing strategy effectiveness, it has received little coverage, mainly because the right combination of data sources has been lacking. Data on consumer attitudes, marketing actions and marketing performance may be available, but the connection between all three types of variables is rarely made. For our demonstration we use data on all three types of variables, measured at the same observation level (the brand, using an identical definition) with the same periodicity. Although such integrated data sources were unusual in the past, consolidations in the market research industry now make this type of integration more easily possible and, in addition, these sources are likely to become more commonly available via the internet.

After a description of our contributions, we begin by proposing four criteria for the analysis of attitude metrics and show how they can be operationalized. In the empirical section, we describe the data set and demonstrate how the relevant parameters can be estimated. Next, we apply our relevance criteria, first for a diagnostic analysis and then for a forward-looking analysis.

Contributions

Our fundamental premise is that the analysis of *intermediate attitude performance metrics* allows us to explain and quantify the observed differences in marketing effectiveness across brands and over time. Our research contributes to the marketing literature in three ways. First, our research provides an empirically testable framework on the conditions under which consumer attitude movements result in sales movements. Traditionally, marketing mix models almost exclusively focus on the response of sales to marketing expenditures in order to derive normative implications for marketing budget setting. This is not sufficient for the brand manager interested in quantifying the linkage between a firm's marketing actions, consumer attitude metrics, and the brand's market performance, as conceptualized in the brand value chain (Keller and Lehmann 2006). Indeed, Srinivasan, Vanhuele and Pauwels (2010) and Stahl et al. (2012) show that such linkages are important in explaining sales. Building on these findings, we address the important question of how financially focused marketing managers can use "soft" mindset metrics to guide marketing mix decisions. We do so by separating out marketing effectiveness in a "*transaction route*" and a "*mindset route*." Furthermore, we quantify the conditions under which the influence of consumer attitudes on sales is strong or weak, the extent of marketing's role in it, and hence how this knowledge can be used to make sound marketing resource allocation decisions.

A second contribution of the paper is the conceptualization of criteria on attitude metrics that identify conditions under which they should be targets of marketing action. We delineate four key criteria – potential, responsiveness, stickiness and sales conversion – that help us determine and understand the connection between marketing actions, attitudinal metrics, and sales outcomes. These criteria stipulate that relevant attitude metrics convert into sales, have potential for growth, have momentum/are sticky and resistant to competitive erosion and respond to marketing stimuli. By applying these criteria we can determine the marketing investment appeal of each marketing instrument. For managers and researchers alike, our criteria, more generally, offer a verifiable explanation for changing marketing elasticities and an actionable connection between marketing and financial performance metrics.

Third, we implement these results for different brands, demonstrating unique mindset-based guidelines for their marketing strategies (i.e. unique by brand, and by time period). We achieve this by estimating mixed-effects response models, which combine fixed and random effects. In particular, *cross-effects models* establish the extent to which the four criteria connecting attitudes to behavior vary over time and across brands. They also indicate what matters more: brand or time variation. In addition, longitudinal *hierarchical linear models* (HLM) examine how marketing-attitude and attitude-sales relations vary by *brand.* We can therefore assess whether, and if so how, one particular brand enjoys higher responsiveness, stickiness and sales conversion of attitude metrics as a result of its marketing efforts. Using our approach, we demonstrate superior results, both in terms of forecast accuracy, and business performance evolution, from using a combined transaction and mindset approach, as compared to using only attitudinal (mindset) or marketing mix (transaction) models.

Table 1 shows a comparative summary of the paper's contributions. Articles prior to 2010 did not use mindset metrics in their marketing mix models. Among the post-2010 articles that do consider mindset metrics, our work is the first to provide criteria for the decomposition of sales effects through mindset metrics and to offer mindset-specific guidelines for improving marketing mix decisions.

--- Insert Table 1 around here ----

Operationalizing the Criteria for Attitude Metrics

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 route' and the latter as the 'transaction route' in Figure 1. We do not propose that purchases can 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.

-- Insert Figure 1 about here ---

To move from an analysis of attitude metrics to recommendations for marketing mix decisions, we have to identify the managerially relevant attitude metrics. Market research firms provide many possible survey based consumer attitudes metrics. However, not all of those can be expected to be relevant for marketing planning for a given brand at a given time. As a case in point, if brand consideration increases as a result of aggressive advertising or promotion, but higher sales or margins do not result, perhaps brand consideration is not a relevant attitudinal metric for this setting. We must therefore provide specific relevance criteria for these metrics. We propose that relevant attitude metrics convert into sales, have potential for growth, are sticky and resistant to competitive erosion, and respond to marketing stimuli.

Sales conversion indicates that an attitudinal metric is associated with sales performance. That, for instance, higher brand consideration is associated with higher sales performance. Sales conversion can be expected to vary in different stages of the purchase funnel, i.e. the lower the funnel stage, the higher the sales conversion. This follows from the hierarchy-of-effects model (Batra and Vanhonacker 1988). For example, a 10% increase in advertising awareness may increase sales by only 3%, whereas a 10% increase in brand liking may increase sales by 6% (Srinivasan et al. 2010). Not accounting for sales conversion runs the risk of silo-marketing, i.e. attitude metrics are viewed as the ultimate performance indicator for marketing, but financial executives have no evidence of marketing's impact on cash flows.

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 or ceiling, 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 ceiling. 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%. Not accounting for potential ignores diminishing return effects, resulting in possible overspending with consequently lower returns. It can also result in missed opportunities on metrics with high potential.

Potential (POT_t) is operationalized as 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

$$POT_t = [\ MAX - Y_t\ ] \ /\ MAX = 0.7. \qquad (1)$$

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 refers to the *staying power* of a change in the attitudinal metric, in the absence of further marketing effort, and possibly in the presence of competitive marketing. 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 the same subset of four brands, 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 higher returns. Not accounting for stickiness may result in myopic decision making and possibly wasteful marketing spending. *Stickiness* (ST_t) is operationalized 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.

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

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 $\varphi_1 = 0.6$ and $\varphi_2 = 0.15$, then stickiness = .75. A priori, we expect consumer attitudinal metrics to be stationary, i.e. 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 also relates to the well-known measure of half-life of a marketing impact.

Responsiveness 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. Not accounting for responsiveness potentially ignores marketing's role in shaping consumer attitudes.

Responsiveness is operationalized as 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:

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

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):

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

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:

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

For example, in an awareness-to-advertising relationship with a response elasticity 0.2 at zero initial awareness, the response elasticity will decline to 0.2*0.6 = 0.12 when awareness reaches 40%.

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 actual vs. stated consumer trial in ten product categories ranging from .009 to 0.896, averaging around 0.5. When historical data are available, conversion metrics may be estimated from a "funnel" model, with metrics such as awareness and preference or liking. However, we do not want to impose a hierarchy-of-effects, because there is little support for such fixed unidirectional hierarchies (e.g. Batra and Vanhonacker 1988; Norris, Peters and Naik 2012). 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.

How do the proposed criteria relate to traditional notions of short-term and long-term marketing elasticity? *Short-term marketing-sales elasticity* is a combination of the marketing responsiveness, the potential and the sales conversion of each metric. Our decomposition allows managers to assess whether e.g. low short-term elasticity is due to low marketing responsiveness versus low inherent potential versus low sales conversion of a metric. Stickiness corresponds to the *carry-over* of marketing effects, so adding this to the other criteria constitutes *long-term* marketing elasticity. As a special case, permanent marketing-sales effects (Dekimpe and Hanssens 1999) arise when a marketing action succeeds in increasing a sales-converting metric that has a stickiness of 1. Finally, our decomposition across metrics allows managers to assess whether a given marketing-sales elasticity is driven by the mindset route through awareness, consideration or liking.

In conclusion, marketing may influence consumer attitudes and this, in turn, may improve the brand's business performance. The degree to which this will occur depends on the nature of the category (for example low vs. high consumer involvement) and on the potential, stickiness, responsiveness and conversion of the attitude metrics. By combining these scores, a brand may obtain an a priori indication of how effective different marketing executions are likely to be. In what follows we apply our framework for different brands in multiple categories varying in consumer involvement level. Our empirical study on multiple brands and categories has two main objectives. First, we provide empirical generalizations about the relationship between attitude and sales criteria; in particular, we examine whether or not the relevance criteria are generic or brand or time specific. Second, we take a brand manager's perspective and examine the extent to which our framework predicts the impact of their marketing mix decisions.

Product Categories, Data, and Modeling

The data come from a brand performance tracker developed by Kantar Worldpanel, which reports the marketing mix, consumer attitude metrics (based on 8,000 households in France) and performance metrics across brands in each category on a four-weekly basis.

For the period between January 1999 and May 2006, we analyze data for the six major brands in each of the four categories, bottled juice, bottled water, cereals, and shampoos. The broad nature of our dataset allows us to investigate whether the extent to which attitude metrics affect sales varies across brands and products. Specifically, as a first validation of our model we verify whether "sales conversion", i.e. the extent to which attitudes translate into purchase behavior (Berger and Mitchell 1989), differs between higher versus lower involvement purchase situations within the studied fast moving consumer goods. Nelson (1970) developed an economic perspective classifying a brand purchase decision as either low involvement, where trial is sufficient, or high involvement, where information search and conviction are required prior to purchase. When product involvement is high, a brand needs to change consumers' hearts and minds in order to overcome consumers' reluctance to change their purchase behavior (Bauer 1967; Peter and Tarpy 1975). Thus, we expect movements in attitudinal metrics to be strongly associated with sales (i.e. there is sales conversion). 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). Here we expect low sales conversion. Marketing actions may have a direct impact on sales without affecting the attitudinal metrics, called the "transaction route" in Figure 1. In our dataset involvement is measured at the category level through several questions including 'product category X is important; you have to be careful when choosing a product'. Shampoo (37.8%) is more involving than juice (29.8%), cereals (28.4%), and bottled water (28.2%).[1] The food-related categories of juice, cereals and bottled water are similar in terms of involvement. The focal brand performance measure is sales volume[2] aggregated across all product forms of each brand (in milliliters or grams). 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,[3] inclusion in the consideration set and brand liking. This selection aimed at covering the three main stages of the purchase funnel. The first two measures refer to the cognitive status of a brand in the consumer's mind, while brand liking obviously refers to the affect status. Two other available measures were not included due to lack of variation (aided brand awareness exhibited ceiling effects) or collinearity ("intention to purchase" correlated highly with consideration set, and the data provider considered the latter to be managerially more useful).

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

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1 Percent agreeing that a buyer has to pay close attention to the product chosen.

2 Although the actual measure of brand performance is purchases, as registered by consumers, and not sales, as registered by stores, we use the word "sales" in the remainder of the paper. Future research should include actual market-level sales data as a dependent variable, particularly if the emphasis is on resource allocation.

3 While awareness typically means 'brand awareness' in marketing theory, recent empirical studies (Lautman and Pauwels 2009; Srinivasan et al. 2010; Pauwels, Erguncu and Yildirim 2013) have shown that instead advertising awareness is a key driver of sales across different industries (drugs, food, drinks, health and beauty) and countries (the U.S. the U.K., France, Brazil). Advertising awareness may be a proxy for brand salience (Tulving and Pearlstone 1966) because it is mainly driven by distribution instead of advertising (Srinivasan et al 2010, table 6). As our data do not contain measures for brand salience, we leave its possible connection with advertising awareness as a promising area for future research.

months.” Our measure gives the percentage of respondents who were aware. 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 the relevant measure. Liking is measured on a seven-point scale (from “like enormously,” to “not at all”), and the measure we use is the average rating. More details on these data sources are described in Srinivasan, Pauwels and Vanhuele (2010).

With a time sample of more than seven years, the presence of different players with different strategies in different product categories, and wide coverage of the marketing mix as well as consumer attitudinal metrics, these data are uniquely suited to address our research questions. The country of investigation is France, which is more homogeneous than large multi-cultural markets such as the US in terms of consumer behavior and retail industry structure.

Econometric Modeling

Our empirical setting covers multiple brands in four different categories, over time. Thus we face some critical questions about the *stability* and the *specificity* of the relationships we seek to estimate. In particular, we need to test if attitude stickiness and sales conversion are stable over time, or are idiosyncratic to certain time periods. In addition, we need to establish if different brands experience different marketing-attitude response effects, or if the effects are generic to the product category. These distinctions are not only econometrically important, they also have different strategic implications. For example, if the attitude-to-sales conversion parameters, including competitive actions, are found to be similar across brands, then no single brand can claim a competitive sales advantage from lifting an attitude metric.[4] Similarly, if an

[4] That is, if competitors match the attitude metric increase. If they do not, a brand can still obtain a competitive advantage from increasing the attitude metric.

attitude-to-sales conversion is unique to a certain time period, then competitive advantage may arise from superior *timing* of a brand's actions.

Table 2 contains an overview of the econometrics models used in estimation.

--- Insert Table 2 about here ---

These models are a combination of attitude and sales response and are estimated as mixed-effects models. This allows us to combine fixed and random effects to separate and investigate how each level affects the attitude criteria (see Appendix A for a technical explanation and model specification choices). First, cross-effects (CRE) models allow random effects to vary both by brand and over time (Baltagi 2005). A typical operationalization is within a cross-sectional/dynamic panel where the cross-sectional factor 'individual' (brand, market etc.) is crossed with the dynamic factor 'time'. In this study's context, CRE models enable us to establish the extent to which the four criteria on translation of attitudes to behavior vary over time and across brands. Second, longitudinal hierarchical linear models (HLM) enable us to investigate how marketing-attitude and attitude-sales relations vary by brand, both in intercept and in the slope of the relationship. We can therefore assess whether higher involvement scenarios imply higher responsiveness, stickiness and sales conversion of attitude metrics. Moreover, the longitudinal HLM model separates the variance of an outcome variable into "among" and "within" variances, which increases the precision of estimates (Rabe-Hesketh and Skrondal 2005).

We estimate the CRE and longitudinal HLM models on logistic-transformed (in equation 4 in Table 2) or log-transformed data (all other equations in Table 2). Due to the large number of equations and parameters that were estimated, we can present only a few illustrative tables and graphs. A full set of econometric results may be found at the web Appendix link.

Generalizations about attitudes and their sales conversion

The CRE and HLM estimation across 24 brands in four categories allows us to make several generalizations on the four criteria that govern the attitude-to-sales relationship. For each of the HLM and CRE models, we test if a mixed-effects specification with both fixed and random effects is superior to a conventional regression with fixed effects only. Tables 3-11 report the main results.

---- Insert Tables 3-11 about here ----

As Tables 5-9 show, the Likelihood Ratio test results are significant for all models, justifying the use of HLM and CRE models.[5] We also compare (i) the varying-intercept (random-intercept) model, and (ii) the varying-intercept and varying-slope (random-intercept and random-slope) model. The information criteria (AIC and BIC) suggest the latter.[6] In order to obtain the brand-level effects, we combine fixed with random effects at the brand level. As a diagnostic check, we perform normal Q-Q plots for the standardized residuals. We find no violation of the normality assumption.[7]

Model Specification test. To test our overall framework (summarized in Figure 1), we conduct a formal mediation analysis, using the Sobel-Goodman mediation test (Sobel 1982) to determine whether a mediator (e.g., attitudinal metric) carries the influence of an independent variable (e.g., marketing action) to the dependent variable, sales. Full mediation would indicate that the attitudinal metrics benchmark model (without marketing-mix) is sufficient to predict sales, as the 'transactions' route of marketing influence is fully subsumed in the 'mindset' route.

5 The LR test results for CRE models are available upon request.

6 The information criteria statistics are available upon request.

7 The normal Q-Q plots are available upon request.

On the other hand, no mediation would indicate that the marketing-mix benchmark model (without attitudinal metrics) is appropriate. Finally, partial mediation would suggest that the full model with both marketing-mix and attitudinal metrics is superior, as it acknowledges both transactions and mindset routes of influence. The Sobel-Goodman tests revealed evidence of partial mediation, leading us to conclude in favor of the full model with both marketing-mix and attitudinal metrics, as shown in Figure 1.[8]

Attitude stickiness and sales conversion are predominantly stable over time. The CRE model results reveal that brand variation is more important than time variation in both attitude stickiness and attitude-to-sales conversion models. Table 3 reports the percentage variation due to brands and time for all these models. We observe that the variation in estimates is more brand-specific than it is time-specific. For example, in the shampoo category, brand SA enjoys a stickiness of consideration and liking that is significantly and substantially higher than that of its competitors, and that persists over time. This result highlights the longevity of the benefits of strong consumer attitudes favoring a brand, and the likely difficulty that competitors might encounter in trying to unseat that brand's position in consumers' minds.[9]

Brand-specific attitude responsiveness to marketing dominates. Turning to the effects of marketing actions on attitude metrics, Table 4 shows they are also more brand-specific than time specific. Attitude responsiveness is typically specific to the brand and stable over time.

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8 In order to test the mediation in a system of equations, we use a Seemingly Unrelated Regressions (SUR) model that allows us to incorporate multiple mediators in a system of equations for brands (with index i) over time (with index t). We estimate the SUR model by the Feasible Generalized Least Square (FGLS) method. The indirect effect coefficients are computed using the nonlinear combination nlcom command in STATA 12; their standard errors are computed using the delta method. Note that these mediation tests are performed based on SUR and not the more complete CRE/HLM models that we report on in the paper. Given this tradeoff, we prefer not to report the full mediation results in the paper. They are available upon request.

9 The statistical results and the time series plots highlighting these findings from the CRE models are available upon request.

Especially brand-specific is attitude responsiveness in the shampoo category: for each attitude metric, the vast majority (63%-80%) of responsiveness variation is due to brands.

Combining all results from the CRE models, we find that attitude criteria are predominantly stable over time, but vary substantially across brands within the same category. Therefore, we proceed by nesting the time variation within the brand variation in longitudinal HLMs to investigate the magnitude of the marketing-attitude and attitude-sales relationships with a view to understanding the nature of competitive brand advantage. The longitudinal HLM results for sales conversion, stickiness and responsiveness are shown in Tables 5-7. We observe differences across brands, but also note general patterns regarding attitude criteria, which can be grouped into two key sets of findings.

The affect metric of liking has high sales conversion but is less sticky while the cognitive metrics of awareness and consideration have low sales conversion but are more sticky. Table 5 shows the liking-to-sales conversion elasticities for each category. The average across all brands is 0.48, implying that *sales move approximately with the square root of liking.* This affective conversion is more than twice the cognitive conversion of awareness and consideration for all categories. However, as shown in Table 6, consumer liking has two less desirable characteristics for brands. First, it is *less sticky* than the cognitive attitude metric awareness. Across the four categories, stickiness for awareness ranges from 0.630 to 0.744 while for liking it ranges from 0.257 to 0.628. Second, as shown in Table 7, brand liking is less responsive to changes in the marketing mix (only 3 significant effects at $p < .05$) relative to awareness (6 significant effects at $p < 0.05$) and consideration (5 significant effects at $p < .05$). Thus marketing has less leverage to change liking versus awareness and consideration.

In contrast to liking, advertising awareness and consideration have low sales conversion: awareness conversions range from 0 to 0.215 while consideration conversions range from 0 to 0.221 (see Table 5). Note that the highest conversions to sales from both awareness (0.215) and consideration (0.221) are in the shampoo category which is higher in consumer involvement than the others. Purchases of low-involvement products are not preceded by significant attitude change, particularly as it pertains to the cognitive attitudinal metrics of awareness and consideration. This shows the limitation of relying only on attitudinal response for making marketing impact inferences. Even when marketing succeeds in lifting an attitudinal metric, it does not imply that this specific attitude metric in turn converts into sales. Accounting for the full chain reaction of events allows for an actionable connection between marketing and financial performance metrics.

Attitude potential is higher for cognitive than for affect metrics. The cognitive metrics of awareness and consideration have higher potential of 73% and 72% while the potential for the affect metric of liking averages 19% (Table 11). This suggests that, all else equal, brands have higher opportunity to make progress on cognitive metrics. Thus consumer satisfaction ("liking") runs high across brands, indicating high product quality and consequently the marketing challenges for individual brands have more to do with their progress in the cognitive metrics.

Assessing Managerial Relevance

Prediction Test. Given that additional costs are involved in the collection of attitudinal data, managers will want to ensure that these data improve the accuracy of sales forecasts, conditional on their marketing plans. We assess these improvements by comparing conditional forecast results for the four-weekly observations 85-96, where the brand's marketing mix decisions for those periods are known (i.e. planned) at the end of period 84. The benchmark forecasts are obtained from the marketing mix models (without attitudinal metrics) reported in Table 8 as well from the attitudinal metrics model (without marketing mix) reported in Table 5. The comparison forecasts are obtained from full models with both marketing-mix and attitudinal metrics reported in Table 9. These models thus allow marketing actions to have both 'transactions' and 'mind-set' route effects on sales.

We proceed with comparisons that are based on one-step ahead and multi-step 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 and strategically valuable in a twelve-month marketing planning scenario. Table 10 shows the comparative results, with a focus on prediction accuracy, as measured by Mean Average Prediction Error (MAPE). Importantly, the sales predictions made by the combined "marketing mix and attitudinal metrics" models outperform the benchmark forecasts obtained using the model with only attitudinal metrics or the model with only marketing mix in most cases. The model combining both marketing mix and consumer attitudinal metrics offers sizeable improvements in prediction: the average MAPE across categories and the two sets of forecasts for the model with attitude metrics is 76.7%, for the marketing mix only model is 68.4%, and the MAPE for the full model is 11.2%. As can be expected, the sales prediction improvements for one-step forecasts are lower since these are more accurate across the board. The sales response model with attitudinal metrics offers superior prediction improvements for categories in which the comparison models are inaccurate. When a benchmark model is already very accurate (e.g. the attitude model for orange juice), for example it has a single-digit MAPE, then the improvement is negligible. Overall, we find that a model with attitudinal metrics and marketing mix outperforms a straight marketing mix model.

Marketing-mix scenarios test. The brand-specificity of results suggests that individual brands face unique circumstances that should govern their marketing moves. Therefore, in theory, we could perform formal optimization of marketing mix spending by brand and by time period as done for example by Fisher et al. (2011b) in the global express delivery sector. However, such an exercise requires the use of brand-specific cost and profit margins as well as a clear understanding of each brand's business objective (for example, share gains versus profit maximization). Absent such financial and strategic information in the current application, we will provide diagnostic information for several brands based on a simulation of different spending scenarios. Using our framework, we diagnose the brands at the beginning of the hold-out period and offer recommendations for changes in the marketing mix, i.e. should the brand pre-existing levels be increased, maintained or cut, with the goal of increasing sales. Then we compare their business outcomes in function of their *actual* marketing spending decisions. For each category, we choose the two top selling brands, SA and SB in shampoo, WA and WB in bottled water, JA and JB in juice, and CA and CB in cereal. Leaving periods 85-96 of our data as a hold-out sample, we summarize the brands' market positions in time period 84. As shown in Table 11, we estimate individual-brand level response models for these focal brands, and examine the shifts in marketing spending that these brands engaged in periods 85-96 to draw conclusions with respect to marketing mix decisions.

As an example of brand diagnostics, the focal **shampoo** brand SA has ample room for mind-set expansion across the board: awareness is 27%, consideration 17%, and liking 71% (5 out of 7); potential for awareness is therefore 73%, consideration is 83% and liking 29%. All three attitudinal metrics have stickiness of over 0.65, and as a result, the brand's prospects in attitudinal space are high, especially when compared to its competitor, shampoo brand B. By contrast, the areas where **bottled water** brand WA has more potential than its competitor WB are less marketing-actionable. For example, WA has more advertising awareness potential and less liking potential than WB (see Table 11). However, the latter matters much more in this low-involvement category. Thus, any marketing effort that stimulates attitude metrics other than liking is likely to have only negligible demand effects.

Two brands implemented strategic shifts in their marketing allocations after T=84. Shampoo brand SA increased its advertising spending by 50%, tripled its promotional spending and kept its prices the same. In contrast, water brand WA cut its advertising spend by 42% and increased its promotion spending by 35%, while also keeping prices the same. What are the consequences of these brands' strategic actions? We make directional sales forecasts up to twelve months later, based on their attitude criteria show in Table 11. As an illustrative example, for shampoo brand SA, there is a high responsiveness of attitudinal metrics to advertising. Specifically, an increase in advertising moves the needle on both the attitudinal metrics of awareness and liking (see Table 11). The awareness metric has ample potential of 73% while the liking metric has potential of 29%. Furthermore, movements in these metrics have high levels of stickiness. Finally, the conversion to sales is high for both awareness and liking as shown in Table 11, resulting in forecasted increase in sales, which we denote with a '↑' in Table 12.

--- Insert Table 12 about here ---

Similar calculations through the chain of events from marketing actions -> attitudinal metrics -> sales conversion are performed for each of the four brands in the analyses. In Table 12, we offer model-based recommendations on changes in marketing mix decisions for promotions versus advertising, i.e. increasing ('↑'), decreasing ('↓') or maintaining ('--') with a view to increasing brand sales. As Table 12 shows, brands that followed the model-based recommendations on marketing mix decisions (as depicted in the column titled "agreement with model-based recommendation on marketing mix decisions") performed better in terms of actual sales outcomes whereas those that followed a different course from our recommendations fared worse. Diagnosing attitudinal brand metrics can help directionally predict the impact of different marketing mix decisions on sales.

Managerial Implications and 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 CFO's needs.

By applying our approach, managers can develop actionable guidelines on how to apply closed-loop learning on the attitude metrics (e.g. "if one observes metrics with the following values/characteristics, then this marketing action will be most effective").

Different product categories and brands within them vary significantly in the magnitude of the four proposed criteria and these differences form the basis for formulating marketing mix strategies that are more likely to succeed (see Table 13). The table provides an overview of four corner cases. The estimates reported in Table 11 allow a classification the brands into the four cells.

---- Insert Table 13 around here----

First, if a brand has low conversion to sales from consumer attitudinal metrics, and low responsiveness to marketing, we label that scenario "*transactions effect at best*." For the 8 brands with 3 attitudinal metrics depicted in Table 11, none of them can be classified into this cell, suggesting that their marketing mix strategies result in sales conversion through the "mindset effect," i.e. *at least one* attitudinal metric/marketing mix combination is sales-relevant for all of these brand scenarios, lending strong support to our current approach.

Turning to the second case, if a brand has low conversion to sales from consumer attitudinal metrics, but high responsiveness to marketing, we label that scenario "*ineffective marketing focus*." For example, brands that invest substantially in consideration-set enhancing advertising, may witness lifts in advertising that do not translate into sales movements. A case in question is water brand WA with respect to advertising and consideration. In contrast, for the same water brand WA, increases in advertising generate awareness lifts that convert to sales. Hence, for water brand WA, an "effective marketing focus" is on the consumer attitudinal metric of awareness rather than consideration.

Third, if the attitudinal metric has high sales conversion but does not respond well to increased marketing spending, that would result in an "*ineffective marketing lever*" scenario. This is the situation that shampoo brand SB finds itself in with regard to sales promotion and consideration. This also applies to shampoo brand SA with respect to sales promotion and awareness. In contrast, increases in shampoo brand SA's advertising generate awareness that converts into sales. Hence, advertising is an "effective marketing lever" for shampoo brand SA to generate sales conversion from a lift to awareness, while promotions are not.

Finally, if the attitude metric has high sales conversion, and there is high responsiveness to marketing, we label that as a situation with "*long-term potential*." For example, water brand

WA has sales conversion from awareness, and awareness has a high responsiveness to all marketing actions. This offers an opportunity to allocate marketing resources to move the needle on the consumer attitudinal metric of awareness and eventually to long-term sales lift.

Our research opens up several avenues for future work. One area is to examine alternative functional forms on the relationship between attitudes and sales. These could be an assessment of the relative performance of log-log models, log-linear models, as well as other forms of non-linearity. Moreover, the effectiveness of marketing actions (e.g., promotions and advertising) could be modeled as functions of awareness, consideration and liking. In addition, while we model potential as the remaining distance to the maximum for its ease with respect to elasticity definitions, future research should compare alternative operationalizations (e.g., square root of the remaining distance to the maximum etc.) as well as alternative models and estimation techniques (e.g., Bayesian Vector Autoregressive Models).

Future research should also 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, etc.) and including that of competitors. Comparisons between brands could also be made in a more systematic way on the basis of their strategic orientation, for instance in terms of their degree of differentiation. 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, Kim and Gajula 2011). Future research should examine which internet-derived attitudinal metrics are the most relevant and investigate the extent to which measurement error in online versus offline metrics may matter. These metrics could then be substituted for the survey based measures that were used in this paper.

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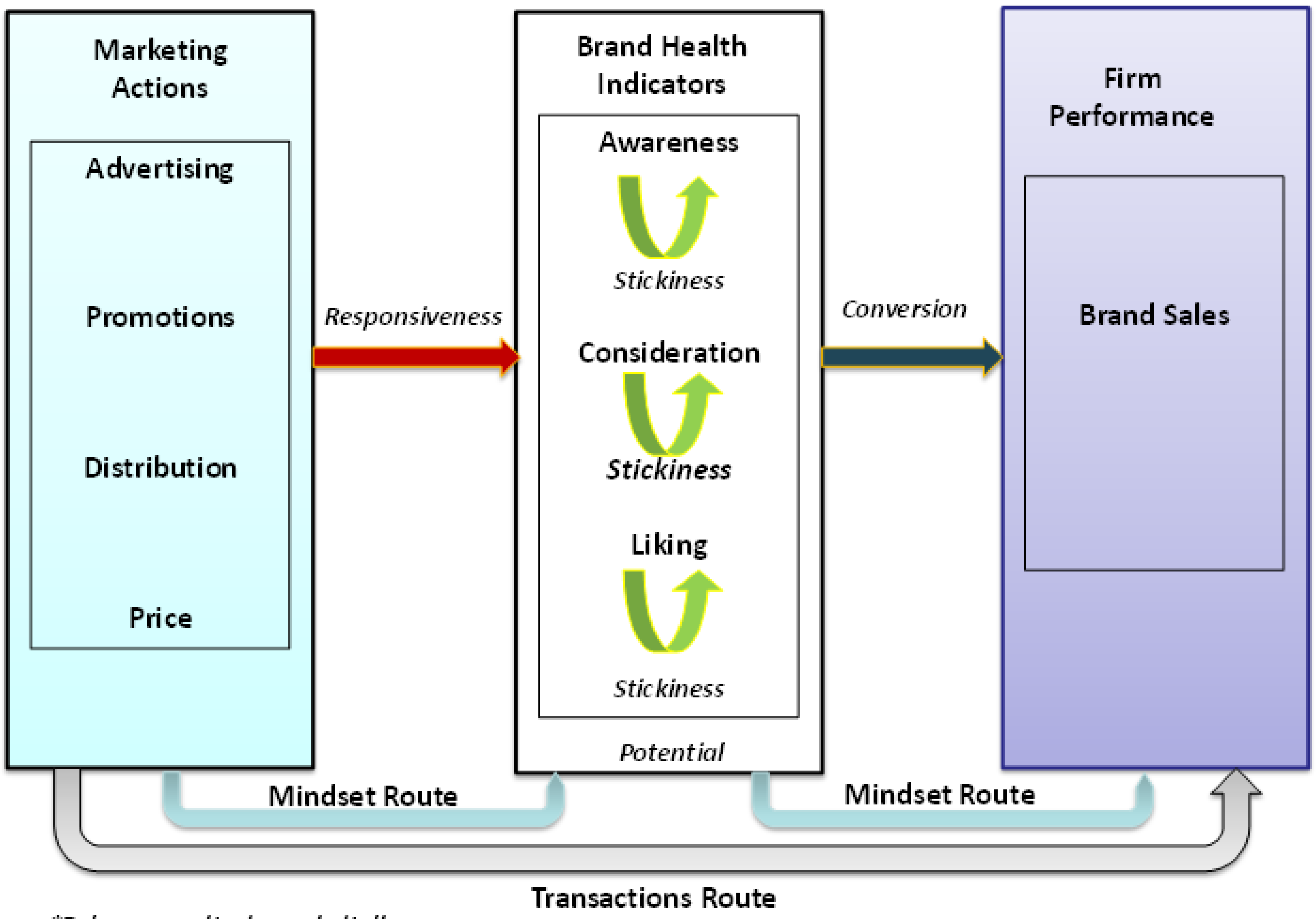
Figure 1: Conceptual Framework



**Relevance criteria are in italics*

Table 1: Comparison of Present Study with Previous Studies

Illustrative Papers	**Marketing Mix Decisions**	**Customer Attitude Metrics**	**Data**	**Research Methodology**	**Criteria for Marketing Mix Decisions**	**Attitudes/ Transaction Decomposition**
Little (1970; 1979)	Yes*	No	No	Sales-advertising Models	No	No
Jedidi et al. (1999)	Yes	No	Nonfood category	Heteroscedastic, varying-parameter joint probit choice and regression quantity model	No	No
Naik et al. (2005)	Yes	No	Detergent brands	Extended Lanchester model, continuous-discrete estimation method	No	No
Pauwels and Hanssens (2007)	Yes	No	Frozen dinner	Time series approach; rolling & recursive-window analyses	No	No
Kumar et al. (2009)	Yes	No	State-level monthly data	Random coefficient Model	No	No
Montoya et al. (2010)	Yes+	No	Pharma data	Hierarchical Bayesian nonhomogeneous hidden Markov model	No	No
Srinivasan et al. (2010)	Yes	Yes	Four grocery categories	Time-series approach (VARX, GFEVD)	No	No
Wiesel et al. (2011)	Yes	No	Furniture firm	Time-series approach (VARX, GIRF)	No	No
Fischer et al. (2011a)	Yes	No	Prescription drugs	Market response models with heuristic rule for optimization	No	No
Fisher et al. (2011b)	Yes	Yes	Delivery service	Choice model with nonlinear optimization	Yes	No
Stahl et al. (2012)	Yes	Yes	Automotive industry	Seemingly unrelated regression; multinomial attraction model	Yes	No
Present study	**Yes**	**Yes**	**Four grocery categories**	**Time-series approach with mixed effects models – HLM and CRE**	**Yes**	**Yes**

Table 2: Overview of Metrics and Models

Metrics/Models	**Equation**	**Model**	**Table**
Potential Metric	Equation (1)	$POT_t = [\ MAX - Y_t\ ] / MAX$	Table 11
Stickiness Metric	Equation (2)	$Y_t = c + \varphi\, Y_{t-1} + \varepsilon_t$	Table 6
Responsiveness Model	Equation (4)	$Y'_t = Y_t\ / (MAX-Y_t) = c\, Y'^{\gamma}_{t-1}\, X_{1t}{}^{\beta}{}_1\ X_{2\,t}{}^{\beta}{}_2\ X_{3t}{}^{\beta}{}_3\ e^u{}_t$	Table 7
Conversion Model (Mindset Route)	Equation (6)	$S_t = cS_{t-1}{}^{\lambda} A_t{}^{\beta}{}_1\, C_t{}^{\beta}{}_2 L_t{}^{\beta}{}_3\, e^u{}_t$	Table 5
Marketing Mix Model (Transactions Route)	Equation (3) applied to sales	$S_t = cS_{t-1}{}^{\gamma} X_{1t}{}^{\delta}{}_1\, X_{2t}{}^{\delta}{}_2 X_{3t}{}^{\delta}{}_3\, e^u{}_t$	Table 8
Transactions + Consumer Attitude Model	Equation (7)	$S_t = cS_{t-1}{}^{\gamma} X_{1t}{}^{\delta}{}_4 X_{2t}{}^{\delta}{}_5\, X_{3t}{}^{\delta}{}_6 A_t{}^{\beta}{}_4 C_t{}^{\beta}{}_5\, L_t{}^{\beta}{}_6\ e^u{}_t$	Table 9

Table 3: Variation across brands & time in attitude stickiness and sales conversion* (CRE)

Shampoo	*Awareness Stickiness*	*Consideration Stickiness*	*Liking Stickiness*	*Sales conversion*
Brand variation	24.37%	62.20%	62.36%	26.22%
Time variation	15.74%	4.78%	8.17%	8.81%
Bottled Water	*Awareness Stickiness*	*Consideration Stickiness*	*Liking Stickiness*	*Sales conversion*
Brand variation	28.65%	60.22%	78.52%	73.74%
Time variation	16.21%	7.26%	4.17%	5.79%
Juice	*Awareness Stickiness*	*Consideration Stickiness*	*Liking Stickiness*	*Sales conversion*
Brand variation	11.55%	49.17%	66.15%	27.76%
Time variation	13.95%	12.68%	4.86%	4.95%
Cereals	*Awareness Stickiness*	*Consideration Stickiness*	*Liking Stickiness*	*Sales conversion*
Brand variation	12.92%	19.34%	23.28%	5.18%
Time variation	21.86%	12.50%	26.40%	17.19%

***** From the cross-effects model output detailed in web appendix, read as: "Of the total variation in the awareness stickiness model in the shampoo category, 24.37% is due to brands, 15.74% due to time, the remainder (59.89%) is residual variation.

Table 4: Variation across brands & time in attitude responsiveness to marketing* (CRE)

Shampoo	*Awareness*	*Consideration*	*Liking*
Brand variation	62.48%	70.86%	80.22%
Time Variation	10.52%	3.75%	4.53%
Bottled Water	*Awareness*	*Consideration*	*Liking*
Brand variation	*44.07%*	*76.76%*	*64.09%*
Time Variation	*12.45%*	*4.29%*	*4.04%*
Juice	*Awareness*	*Consideration*	*Liking*
Brand variation	56.61%	58.15%	54.89%
Time Variation	5.76%	8.15%	5.06%
Cereals	*Awareness*	*Consideration*	*Liking*
Brand variation	32.56%	53.12%	30.82%
Time Variation	15.25%	4.53%	25.49%

***** From the cross-effects model output in web appendix, read as: “Of the total variation in the awareness responsiveness model in the shampoo category, 62.48% is due to brands, 10.52% due to time, the remainder (27.00%) is residual variation.

Table 5: Maximum Likelihood Estimates of Sales Conversion in Longitudinal HLM*

	SHAMPOO CATEGORY			**BOTTLED WATER CATEGORY**		
	Model 1 (DV=Sales)			**Model 1 (DV=Sales)**		
	Coefficient	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*
Fixed Effects						
Constant	**-1.824**	0.415	0.000	0.156	0.377	0.679
AR(1)	**0.544**	0.035	0.000	**0.681**	0.030	0.000
Awareness	**0.215**	0.055	0.000	**0.147**	0.063	0.021
Consideration	**0.221**	0.083	0.008	-0.014	0.059	0.813
Liking	**0.536**	0.275	0.050	**0.466**	0.190	0.014
Random Effects						
$\sqrt{\psi^{(2)}}$	0.0950			0.4867		
$\sqrt{\theta}$	0.1822			0.1100		
$\sigma_{\beta(Awareness)}$	0.0045			0.1221		
$\sigma_{\beta(Consideration)}$	0.0053			0.0148		
$\sigma_{\beta(Liking)}$	0.0142			0.0404		
Log Likelihood	151.440			421.081		
LR test	$\chi^2_4 = 47.69$, $p > \chi^2 = 0.00$			$\chi^2_4 = 70.46$, $p > \chi^2 = 0.00$		
	JUICE CATEGORY			**CEREALS CATEGORY**		
	Model 1 (DV=Sales)			**Model 1 (DV=Sales)**		
	Coefficient	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*
Fixed Effects						
Constant	**-1.279**	0.346	0.000	-0.453	0.251	0.071
AR(1)	**0.690**	0.029	0.000	**0.753**	0.027	0.000
Awareness	**0.100**	0.032	0.002	0.008	0.032	0.811
Consideration	**0.214**	0.061	0.000	**0.143**	0.052	0.006
Liking	**0.561**	0.200	0.005	**0.344**	0.164	0.036
Random Effects						
$\sqrt{\psi^{(2)}}$	0.0572			0.0209		
$\sqrt{\theta}$	0.1367			0.1758		
$\sigma_{\beta(Awareness)}$	0.0086			0.0082		
$\sigma_{\beta(Consideration)}$	0.0088			0.0085		
$\sigma_{\beta(Liking)}$	0.0300			0.0126		
Log Likelihood	314.302			175.711		
LR test	$\chi^2_4 = 47.26$, $p > \chi^2 = 0.00$			$\chi^2_4 = 12.67$, $p > \chi^2 = 0.01$		

*Statistically significant effects at *p<.05* are denoted in **bold.**

$\sqrt{\psi^{(2)}}$ is the standard deviation of the intercept at the brand level, $\sqrt{\theta}$ is the standard deviation of the residuals. $\sigma_{\beta(Consideration)}$ is the standard deviation of the slope parameter for ‘consideration’, $\sigma_{\beta(Liking)}$ is the standard deviation of the slope parameter for ‘liking’, $\sigma_{\beta(Awareness)}$ is the standard deviation of the slope parameter for ‘awareness’.

Table 6: Maximum Likelihood Estimates of Attitude Stickiness in Longitudinal HLM*

	SHAMPOO CATEGORY								
	Model 1 (DV=Awareness)			**Model 2 (DV=Consideration)**			**Model 3 (DV=Liking)**		
	Coefficient	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*
Fixed Effects									
Constant	**7.881**	1.109	0.000	**16.085**	3.053	0.000	**3.222**	0.289	0.000
AR(1)	**0.397**	0.043	0.000	**0.152**	0.055	0.006	**0.260**	0.043	0.000
AR(2)	**0.256**	0.042	0.000	0.122	0.078	0.119	**0.154**	0.042	0.000
Random Effects									
$\sqrt{\psi^{(2)}}$	1.488			6.884			0.230		
$\sqrt{\theta}$	2.664			2.047			0.160		
$\sigma_{AR(1)}$	0.034			0.089			0.023		
$\sigma_{AR(2)}$	0.025			0.161			0.001		
Stickiness	0.653			0.274			0.414		
Log Likelihood	-1231.13			218.22			-1364.64		
LR test	$\chi_3^2 = 94.05$, $p > \chi^2 = 0.00$			$\chi_3^2 = 78.73$, $p > \chi^2 = 0.00$			$\chi_3^2 = 29.79$, $p > \chi^2 = 0.00$		
	BOTTLED WATER CATEGORY								
	Model 1 (DV=Awareness)			**Model 2 (DV=Consideration)**			**Model 3 (DV=Liking)**		
	Coefficient	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*
Fixed Effects									
Constant	**5.795**	1.160	0.000	**11.760**	1.425	0.000	**3.018**	0.271	0.000
AR(1)	**0.497**	0.043	0.000	**0.236**	0.059	0.000	**0.302**	0.044	0.000
AR(2)	**0.240**	0.044	0.000	**0.330**	0.043	0.000	**0.175**	0.043	0.000
Random Effects									
$\sqrt{\psi^{(2)}}$	2.1219			1.7056			0.0939		
$\sqrt{\theta}$	3.5855			2.4568			0.1622		
$\sigma_{AR(1)}$	0.0262			0.1033			0.0396		
$\sigma_{AR(2)}$	0.0398			0.0363			0.0238		
Stickiness	0.737			0.566			0.477		
Log Likelihood	-1532.58			-1324.34			208.27		
LR test	$\chi_3^2 = 21.21$, $p > \chi^2 = 0.00$			$\chi_3^2 = 47.23$, $p > \chi^2 = 0.00$			$\chi_3^2 = 73.87$, $p > \chi^2 = 0.00$		

Table 6 (cont'd)

JUICE CATEGORY									
	Model 1 (DV=Awareness)			**Model 2 (DV=Consideration)**			**Model 3 (DV=Liking)**		
	Coefficient	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*
Fixed Effects									
Constant	**4.023**	0.685	0.000	**14.339**	2.445	0.000	**2.241**	0.265	0.000
AR(1)	**0.496**	0.069	0.000	**0.281**	0.068	0.000	**0.293**	0.040	0.000
AR(2)	**0.248**	0.043	0.000	**0.232**	0.043	0.000	**0.335**	0.040	0.000
Random Effects									
$\sqrt{\psi^{(2)}}$	0.700			5.000			0.198		
$\sqrt{\theta}$	2.825			2.395			0.140		
$\sigma_{AR(1)}$	0.123			0.1353			8.1E-09		
$\sigma_{AR(2)}$	0.027			0.0284			3.1E-09		
Stickiness	0.744			0.513			0.628		
Log Likelihood	-1399.53			-1315.39			293.0046		
LR test	$\chi^2_3 = 11.63, p > \chi^2 = 0.01$			$\chi^2_3 = 53.82, p > \chi^2 = 0.00$			$\chi^2_3 = 39.92, p > \chi^2 = 0.00$		
CEREALS CATEGORY									
	Model 1 (DV=Awareness)			**Model 2 (DV=Consideration)**			**Model 3 (DV=Liking)**		
	Coefficient	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*
Fixed Effects									
Constant	**8.992**	1.991	0.000	**12.249**	2.402	0.000	**4.134**	0.298	0.000
AR(1)	**0.365**	0.050	0.000	**0.251**	0.088	0.004	**0.129**	0.044	0.003
AR(2)	**0.265**	0.066	0.000	**0.237**	0.044	0.000	**0.128**	0.041	0.002
Random Effects									
$\sqrt{\psi^{(2)}}$	4.201			5.197			3.1E-11		
$\sqrt{\theta}$	3.645			3.298			0.264		
$\sigma_{AR(1)}$	0.068			0.190			0.033		
$\sigma_{AR(2)}$	0.125			0.038			1.7E-10		
Stickiness	0.630			0.488			0.257		
Log Likelihood	-1549.73			-1495.69			-59.705		
LR test	$\chi^2_3 = 26.50, p > \chi^2 = 0.00$			$\chi^2_3 = 39.16, p > \chi^2 = 0.00$			$\chi^2_3 = 76.38, p > \chi^2 = 0.00$		

*Statistically significant effects at $p<.05$ are denoted in **bold.**

$\sqrt{\psi^{(2)}}$ is the standard deviation of the intercept at the brand level, $\sqrt{\theta}$ is the standard deviation of the residuals, $\sigma_{AR(1)}$ is the standard deviation of the slope parameter for onelagged dependent variable, $\sigma_{AR(2)}$ is the standard deviation of the slope parameter for two lagged dependent variable.

Table 7: Maximum Likelihood Estimates of Attitude Responsiveness in Longitudinal HLM

SHAMPOO CATEGORY									
	Model 1 (DV=Awareness)			**Model 2 (DV=Consideration)**			**Model 3 (DV=Liking)**		
	Coefficient	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*
Fixed Effects									
Constant	**-0.575**	0.112	0.000	**-1.055**	0.132	0.000	**1.132**	0.179	0.000
AR(1)	**0.431**	0.036	0.000	**0.228**	0.040	0.000	**0.194**	0.042	0.000
Price	**-0.269**	0.114	0.018	-0.086	0.087	0.323	-0.071	0.100	0.481
Promotion	0.028	0.016	0.075	**0.036**	0.017	0.031	0.007	0.021	0.747
Advertising	**0.010**	0.004	0.009	**0.002**	0.001	0.009	0.001	0.001	0.225
Random Effects									
$\sqrt{\psi^{(2)}}$	0.0821			0.1986			0.3318		
$\sqrt{\theta}$	0.1517			0.1273			0.1417		
$\sigma_{\beta(Price)}$	0.1277			0.0150			0.0213		
$\sigma_{\beta(Promotion)}$	0.0179			0.0272			0.0387		
$\sigma_{\beta(Advertising)}$	0.0084			0.0003			0.0012		
Log Likelihood	244.32			347.32			282.38		
LR test	$\chi^2_5 = 110.82,\ p > \chi^2 = 0.00$			$\chi^2_5 = 174.10,\ p > \chi^2 = 0.00$			$\chi^2_5 = 197.43,\ p > \chi^2 = 0.00$		
BOTTLED WATER CATEGORY									
	Model 1 (DV=Awareness)			**Model 2 (DV=Consideration)**			**Model 3 (DV=Liking)**		
	Coefficient	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*
Fixed Effects									
Constant	**-1.050**	0.160	0.000	**-0.881**	0.408	0.031	**0.623**	0.226	0.006
AR(1)	**0.567**	0.031	0.000	**0.247**	0.040	0.000	**0.274**	0.040	0.000
Price	**-0.331**	0.137	0.016	-0.275	0.266	0.302	**-0.552**	0.160	0.001
Promotion	0.033	0.021	0.111	-0.002	0.017	0.889	-0.010	0.026	0.697
Advertising	**0.013**	0.002	0.000	**0.003**	0.001	0.003	**0.004**	0.002	0.029
Random Effects									
$\sqrt{\psi^{(2)}}$	0.1035			0.9369			0.2895		
$\sqrt{\theta}$	0.2096			0.1272			0.2529		
$\sigma_{\beta(Price)}$	0.1766			0.6120			0.1432		
$\sigma_{\beta(Promotion)}$	0.0083			0.0224			0.0079		
$\sigma_{\beta(Advertising)}$	0.0030			0.0006			0.0006		
Log Likelihood	65.69			332.48			-41.03		
LR test	$\chi^2_5 = 62.44, p > \chi^2 = 0.00$			$\chi^2_5 = 175.82, p > \chi^2 = 0.00$			$\chi^2_5 = 149.41, p > \chi^2 = 0.00$		

Table 7 (cont'd)

	Model 1 (DV=Awareness)			Model 2 (DV=Consideration)			Model 3 (DV=Liking)		
JUICE CATEGORY									
	Coefficient	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*
Fixed Effects									
Constant	**-0.503**	0.113	0.000	**-0.816**	0.288	0.005	**0.932**	0.228	0.000
AR(1)	**0.667**	0.027	0.000	**0.382**	0.037	0.000	**0.559**	0.033	0.000
Price	-0.093	0.096	0.332	0.053	0.163	0.743	-0.108	0.179	0.546
Promotion	0.014	0.037	0.702	0.049	0.048	0.307	0.001	0.056	0.996
Advertising	**0.009**	0.002	0.000	**0.002**	0.001	0.050	**0.004**	0.002	0.028
Random Effects									
$\sqrt{\psi^{(2)}}$	0.0400			0.6548			0.2665		
$\sqrt{\theta}$	0.1730			0.1232			0.3288		
$\sigma_{\beta(Price)}$	0.0726			0.3434			0.0762		
$\sigma_{\beta(Promotion)}$	0.0635			0.1030			0.0619		
$\sigma_{\beta(Advertising)}$	0.0047			0.0025			0.0009		
Log Likelihood	170.84			348.50			-188.31		
LR test	$\chi^2_5 = 80.27,\ p > \chi^2 = 0.00$			$\chi^2_5 = 133.18,\ p > \chi^2 = 0.00$			$\chi^2_5 = 83.02,\ p > \chi^2 = 0.00$		
CEREALS CATEGORY									
	Model 1 (DV=Awareness)			**Model 2 (DV=Consideration)**			**Model 3 (DV=Liking)**		
	Coefficient	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*
Fixed Effects									
Constant	**-0.673**	0.197	0.001	**-0.621**	0.129	0.000	**1.388**	0.144	0.000
AR(1)	**0.297**	0.038	0.000	0.067	0.042	0.110	**0.109**	0.041	0.008
Price	0.700	0.491	0.154	**1.094**	0.276	0.000	0.185	0.233	0.427
Promotion	0.067	0.037	0.072	0.043	0.023	0.064	-0.021	0.030	0.489
Advertising	**0.008**	0.003	0.004	0.000	0.003	0.889	0.001	0.004	0.749
Random Effects									
$\sqrt{\psi^{(2)}}$	0.4085			0.2301			0.1517		
$\sqrt{\theta}$	0.2035			0.1784			0.2477		
$\sigma_{\beta(Price)}$	1.1568			0.6114			0.4645		
$\sigma_{\beta(Promotion)}$	0.0805			0.0441			0.0545		
$\sigma_{\beta(Advertising)}$	0.0010			0.0013			0.0028		
Log Likelihood	66.27			147.88			-33.53		
LR test	$\chi^2_5 = 140.05,\ p > \chi^2 = 0.00$			$\chi^2_5 = 208.07,\ p > \chi^2 = 0.00$			$\chi^2_5 = 126.72, p > \chi^2 = 0.00$		

*Statistically significant effects at *p<.05* are denoted in **bold.**

$\sqrt{\psi^{(2)}}$ is the standard deviation of the intercept at the brand level, $\sqrt{\theta}$ is the standard deviation of the residuals. $\sigma_{\beta(price)}$ is the standard deviation of the slope parameter for 'price', $\sigma_{\beta(promotion)}$ is the standard deviation of the slope parameter for 'promotion', $\sigma_{\beta(advertising)}$ is the standard deviation of the slope parameter for 'advertising'.

Table 8: Maximum Likelihood Estimates of Marketing Mix Models (Transactions Route) in Longitudinal HLM

	SHAMPOO CATEGORY			BOTTLED WATER CATEGORY			JUICE CATEGORY			CEREALS CATEGORY		
	Model 1 (DV=Sales)			**Model 1 (DV=Sales)**			**Model 1 (DV=Sales)**			**Model 1 (DV=Sales)**		
	Coefficient	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*
Fixed Effects												
Constant	**0.310**	0.121	0.011	**0.611**	0.158	0.000	**0.276**	0.093	0.003	**0.901**	0.244	0.000
AR(1)	**0.530**	0.036	0.000	**0.717**	0.030	0.000	**0.765**	0.026	0.000	**0.478**	0.034	0.000
Price	**-0.253**	0.106	0.017	**-0.446**	0.085	0.000	**-0.183**	0.071	0.010	-0.018	0.374	0.961
Promotion	**0.113**	0.018	0.000	**0.034**	0.016	0.032	**0.094**	0.022	0.000	**0.094**	0.015	0.000
Advertising	**0.005**	0.001	0.001	0.003	0.002	0.139	**0.004**	0.001	0.000	**0.009**	0.004	0.020
Random Effects												
$\sqrt{\psi^{(2)}}$	0.1072			0.1858			0.0653			0.5284		
$\sqrt{\theta}$	0.1716			0.1146			0.1283			0.1522		
$\sigma_{\beta(Price)}$	0.0196			0.0357			0.0657			0.8779		
$\sigma_{\beta(Promotion)}$	0.0116			0.0233			0.0121			0.0160		
$\sigma_{\beta(Advertising)}$	0.0008			0.0042			0.0013			0.0065		
Log Likelihood	159.668			349.744			303.515			198.533		
LR test	$\chi^2_4 = 38.75$, $p > \chi^2 =$ 0.00			$\chi^2_4 = 61.24$, $p > \chi^2 =$ 0.00			$\chi^2_4 = 21.79$, $p > \chi^2 =$ 0.00			$\chi^2_4 = 89.43$, $p > \chi^2 =$ 0.00		

*Statistically significant effects at *p<.05* are denoted in **bold.** $\sqrt{\psi^{(2)}}$ is the standard deviation of the intercept at the brand level, $\sqrt{\theta}$ is the standard deviation of the residuals. $\sigma_{\beta(price)}$ is the standard deviation of the slope parameter for Price, $\sigma_{\beta(promotion)}$ is the standard deviation of the slope parameter for promotion, $\sigma_{\beta(advertising)}$ is the standard deviation of the slope parameter for advertising.

Table 9: Maximum Likelihood Estimates of Transactions + Consumer Attitude Models in Longitudinal HLM

	SHAMPOO CATEGORY			BOTTLED WATER CATEGORY			JUICE CATEGORY			CEREALS CATEGORY		
	Model 1 (DV=Sales)			Model 1 (DV=Sales)			Model 1 (DV=Sales)			Model 1 (DV=Sales)		
	Coefficient	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*	*Coefficient*	*SE*	*p>|z|*
Fixed Effects												
Constant	**-1.524**	0.394	0.000	0.136	0.380	0.720	**-1.341**	0.286	0.000	-0.276	0.299	0.357
AR(1)	**0.484**	0.037	0.000	**0.583**	0.034	0.000	**0.665**	0.030	0.000	**0.463**	0.034	0.000
Price	**-0.242**	0.083	0.003	**-0.493**	0.117	0.000	**-0.192**	0.048	0.000	-0.154	0.362	0.671
Promotion	**0.104**	0.016	0.000	**0.037**	0.018	0.043	**0.086**	0.020	0.000	**0.085**	0.014	0.000
Advertising	**0.004**	0.001	0.012	0.002	0.002	0.274	**0.003**	0.001	0.001	**0.008**	0.004	0.031
Awareness	**0.136**	0.055	0.014	**0.130**	0.059	0.027	**0.097**	0.024	0.000	0.089	0.047	0.059
Consideration	**0.164**	0.084	0.050	0.013	0.062	0.830	**0.185**	0.058	0.001	0.084	0.062	0.172
Liking	**0.571**	0.267	0.032	0.280	0.200	0.161	**0.550**	0.182	0.003	**0.361**	0.183	0.048
Random Effects												
$\sqrt{\psi^{(2)}}$	0.0284			0.5204			0.0045			0.0693		
$\sqrt{\theta}$	0.1683			0.1087			0.1246			0.1491		
$\sigma_{\beta(Price)}$	0.0135			0.1783			0.0892			0.8389		
$\sigma_{\beta(Promotion)}$	0.0034			0.0312			0.0011			0.0100		
$\sigma_{\beta(Advertising)}$	0.0012			0.0034			0.0003			0.0061		
$\sigma_{\beta(Awareness)}$	0.0047			0.1219			0.0015			0.0488		
$\sigma_{\beta(Consideration)}$	0.0141			0.0112			0.0013			0.0642		
$\sigma_{\beta(Liking)}$	0.0187			0.0263			0.0024			0.2326		
Log Likelihood	172.571			362.746			324.014			208.1782		
LR test	$\chi^2_7 = 22.57$, $p > \chi^2 = 0.00$			$\chi^2_7 = 69.04$, $p > \chi^2 = 0.00$			$\chi^2_7 = 20.91$, $p > \chi^2 = 0.0039$			$\chi^2_7 = 73.31$, $p > \chi^2 = 0.0000$		

*Statistically significant effects at *p<.05* are denoted in **bold.** $\sqrt{\psi^{(2)}}$ is the standard deviation of the intercept at the brand level, $\sqrt{\theta}$ is the standard deviation of the residuals. $\sigma_{\beta(price)}$ is the standard deviation of the slope parameter for price, $\sigma_{\beta(promotion)}$ is the standard deviation of the slope parameter for promotion, $\sigma_{\beta(advertising)}$ is the standard deviation of the slope parameter for advertising, $\sigma_{\beta(Awareness)}$ is the standard deviation of the slope parameter for awareness, $\sigma_{\beta(Consideration)}$ is the standard deviation of the slope parameter for consideration, $\sigma_{\beta(Liking)}$ is the standard deviation of the slope parameter for liking.

Table 10: Predictive Performance for Combined Model vs. Consumer Attitude and Marketing Mix Model

Holdout sample: periods 85 through 96

		Consumer Attitude Model	Marketing Mix Model	Combined Model
One-step	Water	13.8%	8.8%	3.4%
	Shampoo	105.9%	92.3%	23.0%
	Juice	7.8%	8.7%	8.0%
	Cereals	108.3%	99.6%	5.4%
Multi-step	Water	29.1%	22.5%	8.7%
	Shampoo	147.3%	129.3%	22.9%
	Juice	11.7%	13.4%	11.1%
	Cereals	189.4%	172.4%	7.3%

* MAPE denotes the Mean Absolute Percent Error over the 12-month forecast period. One-step ahead forecasts update each consecutive period, while multi-step forecasts predict one to twelve-periods-ahead predictions without updating. Brand-specific results are available from the authors.

Table 11: Diagnostics for two top brands in each category, T=84*

	Awareness																							
	SA			***SB***			***WA***			***WB***			***JA***			***JB***			***CA***			***CB***		
Potential	73%			75%			79%			64%			84%			62%			64%			86%		
Stickiness	0.72			0.60			0.57			0.66			0.73			0.90			0.86			0.77		
Responsiveness	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|
Advertising	**0.141**	0.056	0.012	0.095	0.074	0.202	**0.213**	0.088	0.015	**0.194**	0.088	0.027	0.007	0.044	0.879	0.021	0.044	0.624	**0.513**	0.147	0.001	**2.231**	0.222	0.000
Promotion	0.027	0.020	0.165	0.035	0.022	0.117	**0.034**	0.008	0.000	0.034	0.022	0.125	0.007	0.039	0.867	**0.130**	0.040	0.001	**0.104**	0.038	0.006	**0.148**	0.054	0.006
Price	**-0.259**	0.114	0.023	**-0.273**	0.114	0.017	**-0.332**	0.019	0.000	**-0.328**	0.137	0.016	-0.146	0.105	0.181	-0.137	0.105	0.195	**1.191**	0.241	0.000	0.700	0.491	0.154
Sales Conversion	**0.206**	0.061	0.001	**0.270**	0.015	0.000	**0.145**	0.074	0.048	**0.209**	0.036	0.000	**0.126**	0.040	0.002	0.061	0.041	0.136	**0.027**	0.010	0.009	-0.004	0.035	0.900
	Consideration																							
	SA			***SB***			***WA***			***WB***			***JA***			***JB***			***CA***			***CB***		
Potential	83%			71%			50%			70%			69%			81%			73%			80%		
Stickiness	0.83			0.03			0.57			0.67			0.49			0.75			0.70			0.63		
Responsiveness	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|
Advertising	0.002	0.015	0.915	0.004	0.015	0.806	**1.079**	0.219	0.000	**0.788**	0.227	0.001	0.146	0.200	0.465	**1.237**	0.298	0.000	**0.434**	0.121	0.000	**0.721**	0.176	0.000
Promotion	**0.073**	0.020	0.000	0.044	0.027	0.112	0.001	0.025	0.980	0.016	0.026	0.541	0.056	0.077	0.469	**0.145**	0.053	0.006	**0.067**	0.027	0.013	**0.092**	0.036	0.011
Price	-0.086	0.087	0.323	-0.086	0.087	0.323	-0.275	0.266	0.302	-0.275	0.266	0.302	0.193	0.287	0.503	0.198	0.287	0.490	**1.370**	0.076	0.000	**1.094**	0.276	0.000
Sales Conversion	**0.186**	0.089	0.036	**0.275**	0.010	0.000	-0.023	0.066	0.731	**0.041**	0.013	0.002	**0.199**	0.063	0.002	**0.195**	0.063	0.002	**0.209**	0.007	0.000	**0.154**	0.056	0.006
	Liking																							
	SA			***SB***			***WA***			***WB***			***JA***			***JB***			***CA***			***CB***		
Potential	29%			11%			2%			22%			9%			27%			26%			24%		
Stickiness	0.67			0.00			0.36			0.00			0.51			0.51			0.24			0.18		
Responsiveness	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|	Coeff.	SE	*p*>|*z*|
Advertising	**0.001**	0.001	0.035	0.001	0.021	0.953	0.009	0.123	0.943	0.022	0.097	0.819	**0.019**	0.002	0.000	**0.008**	0.002	0.000	**0.620**	0.147	0.000	0.218	0.191	0.256
Promotion	-0.014	0.064	0.827	-0.014	0.037	0.702	-0.018	0.027	0.495	-0.017	0.027	0.524	0.026	0.059	0.655	-0.037	0.059	0.530	0.065	0.042	0.122	-0.010	0.045	0.819
Price	-0.078	0.100	0.434	-0.078	0.100	0.435	**-0.582**	0.160	0.000	**-0.582**	0.160	0.000	-0.218	0.209	0.298	-0.218	0.209	0.298	0.185	0.233	0.427	0.183	0.233	0.431
Sales Conversion	**0.555**	0.290	0.050	**0.556**	0.084	0.000	**0.494**	0.219	0.024	**0.180**	0.059	0.002	**0.606**	0.211	0.004	**0.603**	0.211	0.004	**0.344**	0.031	0.000	**0.338**	0.174	0.050

*Based on HLM response models. Statistically significant effects at $p<.05$ are denoted in **bold.**

Table12: Illustrations of Model-based Marketing Recommendations and Sales Outcomes

Brand	Advertising spend		Promotional spend		Agreement with model-based recommendations on marketing mix decisions	Sales Outcome	
	Recommend	*Actual*	Recommend	*Actual*		Forecast Conditional on Full Agreement	*Actual*
SA	↑	↑	↑	↑	Full	↑	↑
SB	↓	↓	↓	↑	Partial	↑	--
WA	↑	--	↑	↑	Partial	↑	↓
WB	↑	--	↓	↑	No	↑	↓

* ↑ - denotes an increase; ↓ - denotes a decrease; -- - denoted no change

Table13: Strategic Importance of Attitudinal Metrics

Responsiveness of Attitude to marketing	Sales Conversion	
	Low	**High**
Low	Transactions effect at best	Ineffective marketing lever
High	Ineffective marketing focus	Long-term effect potential

Appendix

Mixed-Effects Models

1. LONGITUDINAL HIERARCHICAL LINEAR MODELS

Hierarchical Linear Models (HLM) provide a more flexible and powerful approach when studying response effects that vary by groups. HLMs are useful when the data are measured at more than one-level (e.g., brands nested within product categories; product categories nested within markets etc.). When the measures are repeated over time the model is called longitudinal HLM (e.g., weekly scores within brand; Rabe-Hesketh and Skrondal 2005). Unlike the traditional OLS regression approach, longitudinal HLM allows us to treat the coefficients of the model as random effects drawn from a normal distribution of possible estimates. This implies that a modeler can detect to what extent the brands vary in the coefficients of interest, intercept and/or slope parameters. In other words, in longitudinal HLM, the random effects in the intercept and/or slope serve to shift the regression line up or down by brand. Additionally, in the longitudinal HLM, the variance of an outcome variable is split into "between" and "within" variances, which increases the precision of estimates.

Model: In our two-level HLM, time series observations within brands constitute the first-level, and the brands form the second-level. We fit the hierarchical linear model to our data, thus combining fixed and random effects. The model is described as follows:

$$y_{it} = \alpha + \beta_{[i]t} X_{it} + \zeta_i^{(2)} + \varepsilon_{it}$$

where the index t is for units (time series observations), i for brands. $\zeta_i^{(2)}$ stands for the random intercept for brands i. ε_{it} is the residual error term for brand i at time t . α is the intercept. $\beta_{[i]t}$ represents that the coefficients of the independent variables X vary across brands. y denotes the dependent variable. Furthermore, we make the following assumptions:

$$\zeta_i^{(2)} \sim N\left(0, \psi^{(2)}\right);\ \varepsilon_{it} \sim N(0, \theta)$$

and the random intercepts and the residual error terms are independent. This model is the 'varying-intercept and varying-coefficient' model. Throughout the paper, we opt for this model formulation since the log likelihood of this specification is always higher than that of 'only varying-intercept' model. Also, the LR test result reveals the same conclusion. We conduct the LR test also to compare the model with one-level ordinary linear regression with two-level model.

Estimation: There are two alternative methods to estimate the parameters of the above model: (i) Maximum Likelihood (MLE) and (ii) Restricted Maximum Likelihood (RMLE). Both methods produce similar regression coefficients. They differ in terms of estimating the variance components, i.e. the latter takes into account the loss of degrees of freedom resulting from the fixed effects (Snijders and Bosker, 1999). Which method to use remains a matter of personal taste (StataCorp 2005, pg. 188). Thus, we fit the model via MLE which is the default in STATA. The estimation technique is iterative and relies on the Expectation-Maximization (EM) algorithm. The convergence is achieved when the error tolerance is met.

Intraclass Correlation: The percentage of observed variation in the dependent variable that can be attributed to the brand-level characteristics is computed by dividing $\psi^{(2)}$ by the total variance:

$$\rho = \frac{\psi^{(2)}}{\psi^{(2)} + \theta}$$

where ρ represents the within-brand correlation, usually referred to as the intraclass correlation coefficient (Hox 2010). The percentage of variance that can be attributed to time-series traits, then, is found by $1 - \rho$. For instance, assuming that we allow for random effects in the stickiness models for both the intercept and the AR(1) and AR(2) coefficients. Then brand-level variance becomes:

$$\rho = \frac{\psi^{(2)} + \sigma^2_{AR(1)} + \sigma^2_{AR(2)}}{\psi^{(2)} + \theta + \sigma^2_{AR(1)} + \sigma^2_{AR(2)}}$$

2. CROSS RANDOM EFFECTS MODELING

In our longitudinal HLM, we treat 'time' as nested within brands. Crossed Random Effects (CRE) modeling assumes that all brands are affected similarly by some events of characteristics associated with the time. A typical example is panel data where the factor 'individual' (brand, market etc.) is crossed with another factor "time" (for a review see Rabe-Hesketh and Skrondal 2005, page 249). Therefore, it is reasonable to deem 'time' as crossed with brands. As with HLM, CRE is a mixed-effects modeling, i.e. we are provided with fixed and random effects parameters.

In CRE modeling, the effects of both brands and time vary (Baltagi, 2005). Hence, by employing CRE, a researcher is able to break down the random effects into two components: 'across brands' and 'over time'.

Model: Specifically, the following equation shows our CRE model:

$$y_{it} = \alpha + \boldsymbol{\beta X}_{it} + \zeta_{1i} + \zeta_{2t} + \varepsilon_{it}$$

where $\zeta_{1i} + \zeta_{2t}$ are random intercepts for brands *i* and time *t*, respectively, and ε_{it} is a residual error term. y represents the dependent variable, α is the intercept term, $\boldsymbol{\beta}$ denotes the estimated fixed effect parameter for the independent variables $\boldsymbol{X}$.

We make the following assumption about the random intercepts:

$$\zeta_1 \sim N(0, \psi_1), \zeta_2 \sim N(0, \psi_2)$$

These random intercepts are not correlated with each other. Furthermore, they are not correlated with the residual error term. Regarding the residual error term, we assume that

$$\varepsilon_{it} \sim N(0, \theta)$$

In this model, the random intercept for brand ζ_{1i} is shared across all time periods for a given brand *i* whereas the random intercept for time period ζ_{2t} is shared by all brands in a given period *t*. The residual error ε_{it} comprises both the interaction between time and brand and any other effect specific to brand *i* in period *t*. An interaction between brand and time might occur since some events in some periods could be more beneficial to some brands than others.

Estimation: As with longitudinal HLM, we use an iterative MLE method that makes use of the EM algorithm.

Intraclass Correlations: We define two intraclass correlations:

(i) One for correlations of observations for the same period across brands:

$$\rho(time) = \frac{\psi_2}{\psi_1 + \psi_2 + \theta}$$

(ii) and one for correlations of observations on the same brand over time:

$$\rho(brand) = \frac{\psi_1}{\psi_1 + \psi_2 + \theta}$$

As a diagnostic check, for both models we use normal Q-Q plots to determine whether or not there is a violation of the normality assumption.

References

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