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# Consumer Attitude Metrics for Guiding Marketing Mix Decisions

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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 data set 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 product categories. We also establish that combining marketing and attitudinal metrics criteria 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 holdout 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.

*Keywords*: consumer attitude metrics; responsiveness; potential; stickiness; sales conversion; hierarchical linear model; cross-effects model; empirical generalizations; dynamic programming model; optimal marketing resource allocation

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## 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 chief financial officer (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.

Marketers work under the assumption that brand health indicators are predictive of later marketing and bottom-line performance but 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%, whereas 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 because of fickle consumers or tough competitors; 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 financial 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 the allocation of resources, can be improved by examining attitude metrics. More specifically, we propose theory-based criteria on these metrics that identify conditions under which they should be targets of marketing action. 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 actions.

After a description of our contributions, we begin by proposing four theory-based 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 using a dynamic programming (DP) analytical model. We conclude with a classification of brands based on the role that attitude metrics play in the connection between marketing actions and sales.

## Contributions

Our research contributes to the marketing literature in four ways (a comparative tabular summary with previous work is provided in Web Appendix C1, available as supplemental material at http://dx.doi.org/10.1287/mksc.2013.0841). First, it 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). Srinivasan et al. (2010) introduced mind-set metrics into standard sales response models and demonstrated that these metrics indeed improve sales response models and are advance indicators of later sales results. Stahl et al. (2012) made a similar demonstration with customer lifetime value.

Second, our research objective is normative, aiming to use the informational value of these mind-set variables for improving marketing decision making. As such, our work is fundamentally different from the mind-set metric article by Srinivasan et al. (2010). The objective of this article was to demonstrate that the explanatory power of a market response model can be increased by adding mind-set metrics. Vector autoregressive (VAR) time-series model estimated there is descriptive and does not lend itself to normative inferences such as deriving optimal advertising spending for a brand. In a VAR model, the marketing (and other) variables are jointly endogenous and their impact is measured as shock effects, both short term and long term. This approach is useful for descriptive and forecasting purposes but not for optimal policy inferences (see Sims 1986 for a detailed discussion in an economic policy context). In the spirit of theory and practice in marketing, our paper builds on these descriptive inferences to (1) describe criteria for monitoring the evolution of brand mind-set metrics and (2) make brand-specific marketing recommendations that are tested in a holdout sample. Because their objective is fundamentally different, Srinivasan et al. do not assess the forecasting accuracy of their models in a holdout sample.

Fischer et al. (2011a) proposed a hierarchical decision model with mind-set metrics and conversion rates to guide marketing resource allocations in a business-to-business (B2B) setting. Their approach is, unfortunately, not applicable for managers in a typical business-to-consumer (B2C) context for three reasons. First, it requires individual-level data, with a high collection cost (at regular intervals with broad market coverage) for B2C manufacturers. As a result, B2C companies rely on syndicated panel data that are only available at an aggregate level. Second, their model assumes a fixed hierarchy-of-effects sequence.

Although this is appropriate for their specific B2B application, where customers follow a standardized purchasing process, such fixed sequences have been invalidated in a B2C context (Batra and Vanhonacker 1988). Third, for their estimations, they develop an ad hoc likelihood function without a closed-form solution. Instead, we use more general econometric estimation techniques. Based on our estimates, we develop a general dynamic programming model that includes sales response (with assumed profit margins) as the outcome variable and the mind-set and marketing mix as input variables. We obtain optimal marketing resource allocation outcomes and demonstrate their optimality by comparing them to actual behavior. In these outcomes, we separate marketing effectiveness in a "transaction route" and a "mind-set route."

A third 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 offer theoretical foundations and 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. By applying these criteria, we can determine the marketing investment appeal of each marketing instrument. For example, if the sales conversion is the same for two brands but one of them obtains sales conversion with less advertising (i.e., it has higher responsiveness), it is possible for that brand to obtain a competitive advantage. 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.

Finally, our mixed-effects response models of the link between marketing actions, attitudes, and sales are well suited for a decision support focus. 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* (HLMs) examine how marketing–attitude and attitude–sales relations vary by *brand*. Using our approach, we demonstrate superior results, in terms of both forecast accuracy and business performance evolution, from using a combined transaction and mind-set approach compared with using only attitudinal (mind-set) or marketing mix (transaction) models.

Our work is the first to provide criteria for the decomposition of sales effects through attitudinal metrics and to offer mind-set-specific guidelines for improving marketing mix decisions.

## Operationalizing the Criteria for Attitude Metrics

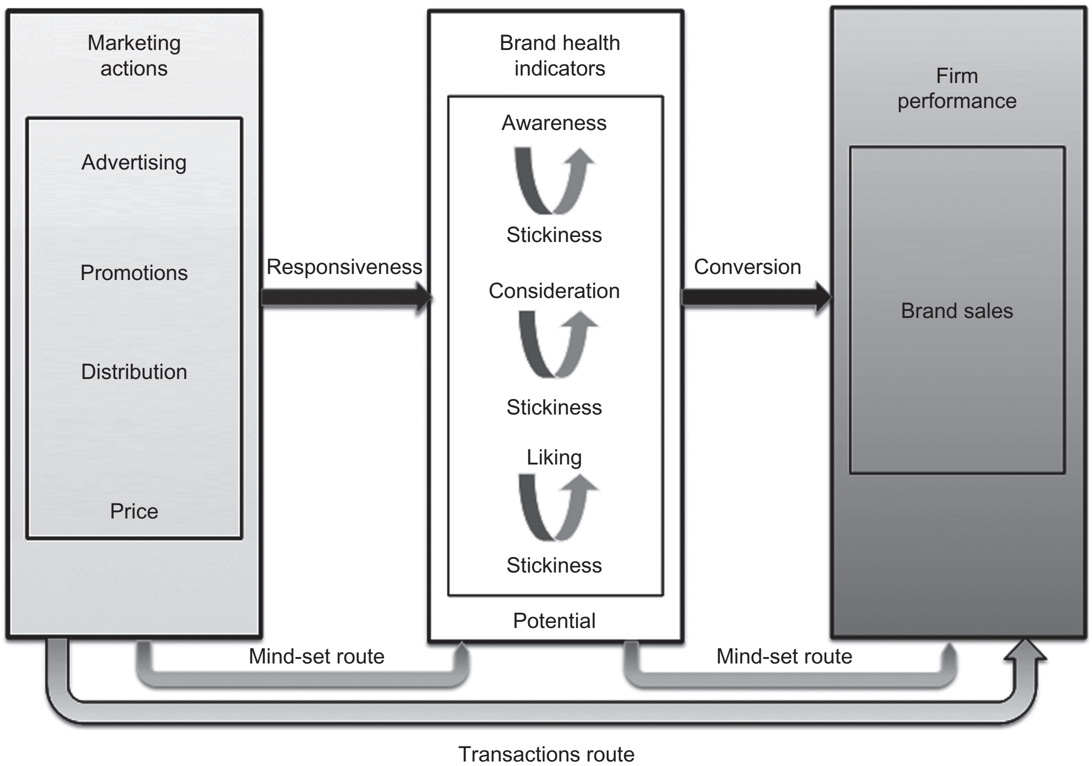
Our conceptual framework, displayed in Figure 1, contrasts marketing effects that occur through changes in attitudinal metrics with those that occur without such changes. We denote the former as the *mind-set route* and the latter as the *transaction route* in Figure 1. We do not propose that purchases 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.

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. We must therefore provide specific relevance criteria for these metrics. We propose that relevant attitude metrics have potential for growth, are sticky and resistant to competitive erosion, respond to marketing stimuli, and convert into sales.

*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.[1] Fourt and Woodlock (1960) 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 affects 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

[1] As noted by Haley and Case (1979), over a large range of attitude scores, their brand share effect can display increasing returns, at least in self-stated consumer interviews (there are no observed sales or market share data in their study). However, our study considers only the leading brands in each category, so we do not have any observations at the lower end of the attitude scales. Therefore, we do not expect to observe increasing returns to attitude changes.

**Figure 1** **Conceptual Framework**




lower returns. It can also result in missed opportunities on metrics with high potential. The theoretical foundation for "potential" comes from market size considerations, where the "market" is defined in attitude space. For example, if 100 individuals comprise a regional market, and 20 of those have prior awareness of brand A, then any marketing campaign aimed at improving brand awareness has the potential of affecting 80 prospects. As the attitude score increases and approaches 100%, the "untapped market size" shrinks, and holding constant the quality of the marketing effort, its anticipated impact will lessen accordingly.

Potential ($\text{POT}_t$) 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 previous awareness $A_{t-1}$ is 30%, then

$$\text{POT}_t = [\text{MAX} - A_{t-1}]/\text{MAX} = 0.7. \qquad (1)$$

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

*Stickiness* refers to the *staying power* as a result of the inertia or lock-in of a change in the attitudinal metric, in the presence of competitive marketing. It captures more than the carryover effect of marketing, as in the decay rate of advertising in the Koyck model (Hanssens et al. 2001). Stickiness is a property of the attitudinal metric: if the metric changes for any reason, how fast does it revert back to its mean? The reasons for such changes may include marketing, competitive marketing, external shocks, etc. 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. The theoretical foundation for "stickiness" comes from memory theory and habit formation theory (Bagozzi and Silk 1983). The results of experiments in social cognition (e.g., Lingle and Ostrom 1979) and consumer behavior (e.g., Kardes 1986) suggest that consumers who process brand attribute information to make evaluative judgments will base subsequent brand evaluations primarily on the recalled judgment rather than the original factual information. In the popular associate network model of the brain, information is "encoded in long-term memory as a pattern of linkages between concept nodes" (Burke and Srull 1988, p. 56). However, brand-related memories may fade over time and as a result of additional learning (e.g., Baumgartner et al. 1983, Belch 1982, Bettman 1979, Schank 1982). Managers need to know the extent of stickiness in the metrics they use; not accounting for stickiness may result in myopic decision making and possibly wasteful marketing spending.

*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 et al. 1994), so an awareness metric may be more responsive to it than a preference metric. The theoretical foundation for "responsiveness" comes from utility theory. If a commercial message or an offer provides a net addition to a consumer's perceived utility from purchasing the associated brand, then a response effect is expected. Note that "net" addition here refers to a comparison of marginal utility versus marginal cost. Marginal cost could be price related (e.g., the willingness to pay more for an advertised brand) or habit related (e.g., the inherent cost associated with taking a risk and switching to a previously unknown brand).

Responsiveness is operationalized as the short-term response of the attitude metric with respect to a marketing stimulus. Furthermore, stickiness is the carryover magnitude in the same response equation. We propose to use a well-established, robust response function to estimate responsiveness. The standard multiplicative response model has the advantage of producing elasticities as responsiveness metrics:

$$A_t = cA_{t-1}^{\gamma} X_{1t}^{\beta_1} X_{2t}^{\beta_2} X_{3t}^{\beta_3} e_t^{u}, \tag{2}$$

where $A$ is the attitudinal metric of awareness as an example and $X_i$ $(i = 1, 2, 3)$ are marketing instruments. Not only does a multiplicative response model provide readily interpretable results, it has also been shown to outperform more complex specifications in forecasting product trials for consumer packaged goods (CPG) (e.g., Hardie et al. 1998). Stickiness is measured through the carryover parameter $\gamma$. For example, if $\gamma = 0.6$, this means that 60% of any change in $A_t$ is carried over to the next period. We expect $\gamma$ to be less than 1 because of memory decay effects that are well documented in psychology (Baddeley et al. 2009).

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 (2) by expressing the dependent variable as an odds ratio (e.g., Johansson 1979):

$$A'_t = A_t/(\mathrm{MAX} - A_t) = cA'^{\gamma}_{t-1} X_{1t}^{\beta_1} X_{2t}^{\beta_2} X_{3t}^{\beta_3} e_t^{u}, \tag{3}$$

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

$$\eta_i = \beta_i \times \mathrm{POT}_t. \tag{4}$$

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

*Sales conversion* indicates that changes in an attitudinal metric convert into sales performance. Sales conversion can be expected to vary in different stages of the purchase funnel; e.g., the lower the funnel stage, the higher the sales conversion. This follows in general from the hierarchy-of-effects model (even if the exact hierarchy may not be fixed; see 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 practice, 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.

The theoretical foundation for "conversion" comes from attitude behavior theory. Although consumers may have awareness of and attitudes toward several brands in a category, they will not necessarily purchase all these brands. Since the behavior (purchasing) is costly, but the attitude is not, attitude behavior conversion will only occur when an attitude change is sufficiently strong. For example, a consumer may report increased ad awareness, consideration, and/or liking for a brand (e.g., because of a new ad campaign) but fail to purchase it in the supermarket for a host of reasons, including a high price or habit inertia for the previously purchased brand.

Conversion rates are typically well below unity; for example, Jamieson and Bass (1989) reported ratios of actual versus stated consumer trial in 10 product categories ranging from 0.009 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. Logically, one might expect that there is a hierarchy among mind-set metrics and that awareness, for instance, leads to consideration. Research on the hierarchy of effects, however, shows that evidence on the exact sequence of effects is mixed (Franses and Vriens 2004, Vakratsas and Ambler 1999). As such, 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 et al. 2012).

Instead, we allow for a multiplicative funnel model that can be applied across conditions. For example, with intermediate attitudinal metrics awareness ($A$), consideration ($C$), and liking ($L$), a multiplicative funnel model for sales revenue ($S$) would be

$$S_t = cS_{t-1}^{\lambda} A_{t-1}^{\beta_1} C_{t-1}^{\beta_2} L_{t-1}^{\beta_3} e_t^{u}. \tag{5}$$

Conversion models such as (5) can be tested either with longitudinal or with mixed cross-sectional time-series data.[2]

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 and the potential and sales conversion of each metric. Our decomposition allows managers to assess whether, for instance, 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 *carryover* 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 mind-set 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 versus high consumer involvement) and on the potential, stickiness, responsiveness, and conversion of the attitude metrics. Each of these criteria is supported by either consumer behavior or market response theory. By combining these scores, a brand may obtain an a priori indication of how effective different marketing campaigns are likely to be. In what follows, we apply our framework for different brands in multiple categories varying in consumer involvement level.

## 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-week basis.

For the period between January 1999 and May 2006, we analyze data for the six major brands in each of these four categories: bottled juice, bottled water, cereal, and shampoo. The broad nature of our data set 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 from attitudes into purchase behavior 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 to overcome consumers' reluctance to change their purchase behavior (Bauer 1967, Peter and Tarpey 1975). In such cases, 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 choose a brand simply because it is available or promoted, without having fundamentally changed their opinion about it. This low involvement path is compatible with Ehrenberg's (1974) awareness-trial-reinforcement model. In such cases, we expect low sales conversion.

Marketing actions may have a direct impact on sales without affecting the attitudinal metrics; this is called the transaction route in Figure 1. In our data set, involvement is measured at the category level through several items, including "product category $X$ is important; you have to be careful when choosing a product." The results show that shampoo (37.8%) is more involving than the food and beverage categories juice (29.8%), cereal (28.4%), and bottled water (28.2%),[3] which have minimal variation. The focal brand performance measure is sales volume[4] 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.

[2] To avoid correlated errors stemming from the use of mind-set variables both as dependent variables (Equation (3)) and as predictors, we used the first lagged mind-set variables as predictors in the "sales conversion" model (Equation (5)). This approach is intuitive, as attitudes logically precede choices; i.e., consumers enter the purchase occasion with a preexisting attitude, then combine that with the prevailing marketing mix conditions (prices, promotion, etc.) and make a decision.

[3] We show the percentge agreeing that a buyer has to pay close attention to the product chosen.

[4] 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.

After a discussion with the data provider, we selected the following three measures from the available attitudinal metrics: advertising awareness,[5] 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, whereas brand liking obviously refers to the affect status. Two other available measures were not included for lack of variation, aided brand awareness (which exhibited ceiling effects) and collinearity (intention to purchase correlated highly with the 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 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.[6] More details on these data sources are described in Srinivasan et al. (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 multicultural markets such as the United States in terms of consumer behavior and retail industry structure.

[5] Whereas awareness typically means "brand awareness" in marketing theory, recent empirical studies (Lautman and Pauwels 2009, Pauwels et al. 2013, Srinivasan et al. 2010) have shown that advertising awareness is a key driver of sales across different industries (e.g., drugs, food, drinks, health, beauty) and countries (e.g., the United States, the United Kingdom, France, Brazil). Intuitively, advertising awareness is important because consumers are exposed to hundreds of ads daily and can recall only a fraction of them (Burke and Srull 1988). Moreover, previous studies found that advertising awareness also increased with factors other than advertising (Table 6 in Srinivasan et al. 2010). Thus, advertising awareness may be a proxy for brand salience (Tulving and Pearlstone 1966). Because our data do not contain measures for brand salience, we leave its possible connection with advertising awareness as a promising area for future research.

[6] The asymmetry in the brand liking versus brand consideration and ad awareness scales is typical for commercially available attitude measurement. However, it may partially explain high average scores for brand liking (as the typical respondent answers the question for each brand) compared with ad awareness and consideration (because the respondent needs to put the effort into clicking on the brand from a list of all other brands in the category).

**Econometric Modeling**

Our empirical setting covers multiple brands in four different categories over time. Thus we face some critical questions about the stability and specificity of the relationships we seek to estimate. In particular, we need to test whether attitude stickiness and sales conversion are stable over time or are idiosyncratic to certain time periods. In addition, we need to establish whether 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, though a brand can achieve an advantage if it can lift an attitude metric efficiently.

Our response models focus on brand-level response to marketing and attitudinal variables. Naturally, these actions and attitudes take place in a competitive environment. Our parameter estimates implicitly control for competitive effects because the dependent variables are real-world observations. Thus, brand sales lifts are implicitly bounded by total category demand and consumer loyalty for competing brands. We choose not to include formal competitive models (e.g., equations reflecting individual competitive behavior and/or market share models) because the sectors under study (shampoo, cereal, fruit juice, and bottled water) are mature, with several important brands competing in each time period. There is always at least one brand promoting or advertising; thus competition is stable at the category level. Furthermore, research in similar markets (see Steenkamp et al. 2005 for a study on more than 1,200 European CPG brands) has shown that the predominant competitive reaction in advertising or promotion is no reaction at all. We leave the formal inclusion of brand-level competition as an area for future research. Table 1 contains an overview of the econometrics models used in estimation.

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 Web 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 or dynamic panel where the cross-sectional dimension (brand, market, etc.) is crossed with the dynamic factor "time." In this study's context, CRE models enable us to establish the extent

**Table 1 Overview of Metrics and Models**

| Metrics/models | Equation | Model | Table |
|---|---|---|---|
| Potential metric | Equation (1) | $\mathrm{POT}_t = [\mathrm{MAX} - A_{t-1}]/\mathrm{MAX}$ | Table 8 |
| Stickiness metric | Equation (3) | $A'_t = A_t/(\mathrm{MAX} - A_t) = cA'^{\gamma}_{t-1} X^{\beta_1}_{1t} X^{\beta_2}_{2t} X^{\beta_3}_{3t} e^u_t$ | Table 8 |
| Responsiveness model | Equation (3) | $A'_t = A_t/(\mathrm{MAX} - A_t) = cA'^{\gamma}_{t-1} X^{\beta_1}_{1t} X^{\beta_2}_{2t} X^{\beta_3}_{3t} e^u_t$ | Table 4 |
| Conversion model (mind-set route) | Equation (5) | $S_t = cS^{\lambda}_{t-1} A^{\beta_1}_{t-1} C^{\beta_2}_{t-1} L^{\beta_3}_{t-1} e^u_t$ | Table 3 |
| Marketing mix model (transactions route) | Equation (2) applied to sales | $S_t = cS^{\gamma}_{t-1} X^{\delta_1}_{1t} X^{\delta_2}_{2t} X^{\delta_3}_{3t} e^u_t$ | Table 5 |
| Transactions + Consumer attitude model[a] | Equation (6) | $S_t = cS^{\gamma}_{t-1} X^{\delta_4}_{1t} X^{\delta_5}_{2t} X^{\delta_6}_{3t} A^{\beta_4}_{t-1} C^{\beta_5}_{t-1} L^{\beta_6}_{t-1} e^u_t$ | Table 6 |

[a]Equation (6) combines Equations (2) and (5) and has both marketing mix and attitudinal metrics.

to which the four criteria on translation of attitudes to behavior vary over time and across brands. Second, longitudinal hierarchical linear models (HLMs) enable us to investigate how marketing–attitude and attitude–sales relations vary by brand. We can therefore assess whether higher involvement scenarios imply higher responsiveness, stickiness, and sales conversion of attitude metrics. Moreover, the longitudinal HLM 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 HLMs on logistic-transformed (in Equation (3) in Table 1) or log-transformed (all other equations in Table 1) data. To select the final empirical model, we perform several tests based on our HLM and CRE model formulations (see Equations (A1) and (A4) in Web Appendix A). We discuss the results of these tests in the ensuing section in detail. Because of the large number of equations and parameters that were estimated, we present only a few illustrative tables and graphs. A full set of econometric results may be found in the Web appendix.

## Estimation Results

### Model Testing

The CRE and HLM estimations across 24 brands in four categories allow us to make several generalizations on the four criteria that govern the attitude-to-sales relationship. For each of the HLMs and CRE models, we test whether a mixed-effects specification with both fixed and random effects is superior to a conventional regression with fixed effects only. Tables 2–8 report the main results.

As Tables 3–6 show, the likelihood ratio (LR) test results are significant for all models, justifying the use of HLMs and CRE models.[7] We also compare (i) the varying intercept model and (ii) the varying intercept and varying slope model. The information criteria (Akaike's information criteria and Bayesian information criteria) support the latter.[8] To obtain the brand-level effects, we combine fixed and 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.[9]

**Mediation 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 "transaction" route of marketing influence is fully subsumed in the "mind-set" route. 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 because it acknowledges both transactions and mind-set routes of influence. The Sobel–Goodman tests obtained using the HLM estimation results revealed evidence of partial mediation (see Web Appendix C2 for results), leading us to conclude in favor of the full model with both marketing mix and attitudinal metrics, as shown in Figure 1.

**Endogeneity Test.** The model we use is subject to a potential endogeneity issue as a result of lagged regressors and the brand-level random-effects term. To deal with this, we use the dynamic panel model developed by Arellano and Bond (1991), using a generalized method of moments (GMM) estimator that relies on constructing moment conditions based on

[7] The LR test results for CRE models are available from the authors upon request.

[8] The information criteria statistics are available from the authors upon request.

[9] The normal $Q$–$Q$ plots are available from the authors upon request.

the lagged variables.[10] The results indicate that the dynamic panel estimates are similar to those of longitudinal HLMs in terms of sign and significance.[11] We conclude that accounting for endogeneity does not impact our substantive findings, and we report the HLM results. These estimates offer superior properties over dynamic panel estimation, including the ability to detect to what extent the groups (brands) vary in the intercept and/or slope parameters and the ability to obtain estimates for the category level brand level simultaneously. Furthermore, the variance of the dependent variable is split into "between" and "within" variances, which increases the precision of estimates.

### Generalizations About Attitudes and Their Sales Conversion

We organize our findings around the four criteria of stickiness, conversion, marketing responsiveness, and potential.

**Sales Conversion Is Predominantly Stable Over Time.** The CRE model results reveal that brand variation is more important than time variation in attitude-to-sales conversion models. Table 2 reports the percentage variation due to brands and time for all these models. Except for the cereal category, we observe that the variation in estimates is more brand specific than time specific. This result highlights the benefit of strong consumer attitudes favoring a brand and resulting in sales conversion.[12]

**Brand-Specific Attitude Responsiveness to Marketing Dominates.** Turning to the effects of marketing actions on attitude metrics, Table 2 shows they are also more brand specific than time specific. Attitude responsiveness is typically specific to the brand and stable over time. This is especially pronounced 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.[13] 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 and responsiveness are shown in Tables 3 and 4, respectively. We observe differences across brands but also note general patterns regarding attitude criteria, which can be grouped in two key sets of findings.

**Sales Conversion vs. Stickiness for Liking vs. Awareness and Consideration.** Table 3 shows the liking-to-sales conversion elasticities for each category. The median across all brands is 0.549, implying that *sales move approximately with the square root of liking*. This affect conversion is more than three times the cognitive conversion of consideration for all categories. However, as shown in Table 4, consumer liking has two less desirable characteristics for brands. First, it is *less sticky* than the cognitive attitude metric of awareness. Across the four categories, the median level of stickiness for awareness is 0.499, whereas that for consideration is 0.238 and for liking is 0.234. Second, as shown in Table 4, brand liking is responsive to advertising in only two of the four categories, whereas consideration is responsive to advertising in all but one category. Advertising moves the needle on all three mind-set metrics of awareness, consideration, and liking; 9 of the 12 coefficients are statistically significant. Price moves the needle on awareness, consideration, and liking, though only 4 of the 12 responsiveness coefficients are statistically significant. Promotion influences consideration only for the shampoo category. Liking has high sales conversion ranging from 0.403 to 0.926, whereas consideration has lower sales conversion: consideration conversions range from 0 to 0.193 (see Table 3). Note that the highest conversions to sales from both consideration (0.193) and liking (0.926) are in the shampoo category, which is higher in consumer involvement than the others.

These results may be explained by consumer behavior theory. Feldman and Lynch's (1988) accessibility–diagnosticity framework predicts that a given piece of information "will be used as an input to a subsequent response if the former is accessible and if

[10] Their approach is as follows: first, take first differences of both sides and eliminate the group effects ($u_i$), then look for instrumental variables (lagged variables), and finally, use GMM to estimate the model. We implemented these steps and compared the results of the dynamic panel GMM estimations with the results of longitudinal HLMs.

[11] These are available from the authors upon request.

[12] The statistical results and the time-series plots highlighting these findings from the CRE models are available from the authors upon request.

[13] These variations across brands may be due to several factors such as the quality of the product experience, past market spending, and market share. Our data only allow us to check the correlation of the latter variable with the attitude criteria across brands. The only substantial correlation is that between market share and advertising awareness conversion (0.29). Thus, large brands tend to have a higher sales conversion of ad awareness. A plausible rationale is that, once they notice a brand's advertising, consumers have an easier time remembering, finding, and buying larger versus smaller brands. This is consistent with the double jeopardy effect (Ehrenberg et al. 1990).

**Table 2** Variation Across Brands and Time in Attitude Responsiveness to Marketing and Sales Conversion: CRE

| Category | Awareness responsiveness (%) | Consideration responsiveness (%) | Liking responsiveness (%) | Sales conversion (%) |
|---|---|---|---|---|
| Shampoo | | | | |
| Brand variation | 62.48 | 70.86 | 80.22 | 15.14 |
| Time variation | 10.52 | 3.75 | 4.53 | 6.47 |
| Bottled water | | | | |
| Brand variation | 44.07 | 76.76 | 64.09 | 71.71 |
| Time variation | 12.45 | 4.29 | 4.04 | 6.30 |
| Juice | | | | |
| Brand variation | 56.61 | 58.15 | 54.89 | 22.93 |
| Time variation | 5.76 | 8.15 | 5.06 | 4.74 |
| Cereal | | | | |
| Brand variation | 32.56 | 53.12 | 30.82 | 6.35 |
| Time variation | 15.25 | 4.53 | 25.49 | 17.81 |

*Note.* From the cross-effects model output in the Web appendix, read as follows: "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 3** Maximum Likelihood Fixed Effects Estimates of Sales Conversion in Longitudinal HLM

| | Shampoo | | | Bottled water | | | Juice | | | Cereal | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | SE | $p > \|z\|$ | Coefficient | SE | $p > \|z\|$ | Coefficient | SE | $p > \|z\|$ | Coefficient | SE | $p > \|z\|$ |
| Fixed effects | | | | | | | | | | | | |
| *Constant* | −1.722* | 0.414 | 0.000 | 0.273 | 0.384 | 0.477 | −1.271* | 0.344 | 0.000 | −0.617* | 0.258 | 0.017 |
| *AR*(1) | 0.569* | 0.035 | 0.000 | 0.678* | 0.031 | 0.000 | 0.711* | 0.030 | 0.000 | 0.743* | 0.028 | 0.000 |
| *Awareness* $(t-1)$ | 0.011 | 0.056 | 0.845 | 0.013 | 0.029 | 0.667 | 0.055 | 0.032 | 0.080 | 0.006 | 0.032 | 0.844 |
| *Consideration* $(t-1)$ | 0.193* | 0.085 | 0.023 | −0.017 | 0.059 | 0.773 | 0.193* | 0.061 | 0.002 | 0.145* | 0.052 | 0.002 |
| *Liking* $(t-1)$ | 0.926* | 0.414 | 0.000 | 0.403* | 0.191 | 0.035 | 0.641* | 0.201 | 0.001 | 0.457* | 0.152 | 0.003 |
| LR test | $\chi^2_4 = 35.64$, $p > \chi^2 = 0.00$ | | | $\chi^2_4 = 33.40$, $p > \chi^2 = 0.00$ | | | $\chi^2_4 = 36.96$, $p > \chi^2 = 0.00$ | | | $\chi^2_4 = 14.61$, $p > \chi^2 = 0.01$ | | |

*Notes.* The dependent variable is *sales*. $t-1$ indicates one lag is taken. Because of space limitations, random effects estimates are in Table C3 in the Web appendix.
*Statistically significant effects at $p < 0.05$.

it is perceived to be more diagnostic than other accessible inputs" (p. 431). The greater the accessibility and diagnosticity of an input for a judgment relative to alternate inputs, the greater the likelihood that it will be used (Simmons et al. 1993). In high involvement categories, such as shampoo, attitudinal changes in consideration make the consumer's brand experience diagnostic and accessible resulting in higher sales conversion. Purchases of low involvement products, on the other hand, 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%, respectively, whereas the potential for the affect metric of liking averages 19% (see Table 8). For instance, some consumers who are not considering a brand may well have tried it and not liked it, resulting in higher potential for consideration relative to liking. 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 monthly observations of periods 85–96, where the brand's marketing mix decisions for those periods are known

**Table 4 Maximum Likelihood Fixed Effects Estimates of Attitude Responsiveness in Longitudinal HLM**

| | Model 1 (DV = *Awareness*) | | | Model 2 (DV = *Consideration*) | | | Model 3 (DV = *Liking*) | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | SE | $p > \lvert z \rvert$ | Coefficient | SE | $p > \lvert z \rvert$ | Coefficient | SE | $p > \lvert z \rvert$ |
| | | | | Shampoo | | | | | |
| 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 |
| 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 | | | | | |
| 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 |
| LR test | $\chi^2_5 = 62.44$, $p > \chi^2 = 0.00$ | | | $\chi^2_5 = 175.82$, $p > \chi^2 = 0.00$ | | | $\chi^2_5 = 149.41$, $p > \chi^2 = 0.00$ | | |
| | | | | Juice | | | | | |
| 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 | 0.054 | 0.004* | 0.002 | 0.028 |
| LR test | $\chi^2_5 = 80.27$, $p > \chi^2 = 0.00$ | | | $\chi^2_5 = 133.18$, $p > \chi^2 = 0.00$ | | | $\chi^2_5 = 83.02$, $p > \chi^2 = 0.00$ | | |
| | | | | Cereal | | | | | |
| 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 |
| LR test | $\chi^2_5 = 140.05$, $p > \chi^2 = 0.00$ | | | $\chi^2_5 = 208.07$, $p > \chi^2 = 0.00$ | | | $\chi^2_5 = 126.72$, $p > \chi^2 = 0.00$ | | |

*Notes.* Because of space limitations, random effects estimates are in Table C4 in the Web appendix. DV, dependent variable.
*Statistically significant effects at $p < 0.05$.

(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 5, as well as from the attitudinal metrics model (without marketing mix) reported in Table 3. The comparison forecasts are obtained from full models with both marketing mix and attitudinal metrics reported in Table 6. These models thus allow marketing actions to have both transaction and mind-set route effects on sales.

We proceed with comparisons that are based on one-step ahead and multistep forecasts, i.e., projections up to 12 periods ahead. Although the one-step forecasts are expected to be more accurate, the multistep predictions are more realistic and strategically valuable in a 12-month marketing planning scenario. Table 7 shows the comparative results, with a focus on prediction accuracy, as measured by mean absolute percentage 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 all cases. The combined model offers sizeable improvements in prediction: across categories and forecast horizons, the average MAPE for the attitude model is 15.7%, for the marketing mix-only model is 17.7%, and for the combined model is 12.0%. As can be expected, the sales prediction improvements for one-step forecasts are lower because these are more accurate in the benchmark models.

**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 period, as done, for example, by Fischer et al. (2011a) in the global express delivery sector.

**Table 5 Maximum Likelihood Fixed Effects Estimates of Marketing Mix Models (Transaction Route) in Longitudinal HLM**

| | Shampoo | | | Bottled water | | | Juice | | | Cereal | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 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 |
| LR test | $\chi^2_4 = 38.75$, $p > \chi^2 = 0.00$ | | | $\chi^2_4 = 61.24$, $p > \chi^2 = 0.00$ | | | $\chi^2_4 = 21.79$, $p > \chi^2 = 0.00$ | | | $\chi^2_4 = 89.43$, $p > \chi^2 = 0.00$ | | |

*Notes.* The dependent variable is *sales*. Because of space limitations, random effects estimates are in Table C5 in the Web appendix.
*Statistically significant effects at $p < 0.05$.

**Table 6 Maximum Likelihood Fixed Effects Estimates of Transactions + Consumer Attitude Models in Longitudinal HLM**

| | Shampoo | | | Bottled water | | | Juice | | | Cereal | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coefficient | SE | $p > \|z\|$ | Coefficient | SE | $p > \|z\|$ | Coefficient | SE | $p > \|z\|$ | Coefficient | SE | $p > \|z\|$ |
| Fixed effects | | | | | | | | | | | | |
| *Constant* | −1.443* | 0.402 | 0.000 | −0.026 | 0.343 | 0.939 | −1.460* | 0.280 | 0.000 | −0.610* | 0.309 | 0.048 |
| *AR*(1) | 0.420* | 0.036 | 0.000 | 0.658* | 0.031 | 0.000 | 0.658* | 0.029 | 0.000 | 0.503* | 0.032 | 0.000 |
| *Price* | −0.366* | 0.096 | 0.000 | −0.443* | 0.111 | 0.000 | −0.202* | 0.050 | 0.000 | −0.209 | 0.266 | 0.433 |
| *Promotion* | 0.127* | 0.016 | 0.000 | 0.038* | 0.019 | 0.048 | 0.098* | 0.020 | 0.000 | 0.088* | 0.015 | 0.000 |
| *Advertising* | 0.005* | 0.001 | 0.000 | 0.004* | 0.002 | 0.040 | 0.004* | 0.001 | 0.000 | 0.009* | 0.003 | 0.003 |
| *Awareness* $(t-1)$ | 0.035 | 0.054 | 0.510 | 0.080 | 0.050 | 0.108 | 0.086* | 0.024 | 0.000 | 0.033 | 0.041 | 0.417 |
| *Consideration* $(t-1)$ | 0.166* | 0.079 | 0.050 | 0.009 | 0.058 | 0.876 | 0.156* | 0.056 | 0.006 | 0.168* | 0.069 | 0.014 |
| *Liking* $(t-1)$ | 0.897* | 0.261 | 0.001 | 0.317 | 0.189 | 0.092 | 0.674* | 0.176 | 0.000 | 0.426* | 0.138 | 0.002 |
| LR test | $\chi^2_7 = 36.13$, $p > \chi^2 = 0.00$ | | | $\chi^2_7 = 47.89$, $p > \chi^2 = 0.00$ | | | $\chi^2_7 = 22.92$, $p > \chi^2 = 0.01$ | | | $\chi^2_7 = 82.10$, $p > \chi^2 = 0.00$ | | |

*Notes.* The dependent variable is *sales*. $t-1$ indicates one lag is taken. Because of space limitations, random effects estimates are in Table C6 in the Web appendix.
*Statistically significant effects at $p < 0.05$.

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 holdout period and offer recommendations for changes in the marketing mix, i.e., should the brand's preexisting marketing support 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 holdout sample, we summarize the brands' market positions in time period 84. As shown in Table 8, we estimate individual brand-level response models for these focal brands and examine the shifts in marketing spending that these brands experienced in periods 85–96 to draw conclusions regarding marketing mix decisions.

**Table 7 Predictive Performance (MAPE) for the Combined Model vs. the Consumer Attitude and Marketing Mix Models (Holdout Sample: Periods 85–96)**

| Forecast solution | Category | Consumer attitude model (%) | Marketing mix model (%) | Combined model (%) |
|---|---|---|---|---|
| One-step ahead | Shampoo | 27.63 | 29.28 | 26.37 |
| | Bottled water | 6.62 | 5.05 | 3.31 |
| | Juice | 9.33 | 9.92 | 9.02 |
| | Cereal | 5.86 | 7.54 | 3.81 |
| Multistep ahead | Shampoo | 33.13 | 37.77 | 26.50 |
| | Bottled water | 16.67 | 15.69 | 10.79 |
| | Juice | 16.98 | 23.32 | 9.05 |
| | Cereal | 9.74 | 12.84 | 7.24 |

*Notes.* One-step ahead forecasts update each consecutive period, whereas multistep forecasts predict 1–12 periods ahead without updating. MAPE denotes the mean absolute percentage error over the 12-month forecast period.

As an example of brand diagnostics, shampoo brand SA has ample room for mind-set expansion across the board: awareness is 27%, consideration 17%, and liking 71% (5 of 7); potential for awareness is therefore 73%, consideration 83%, and liking 29%. As a result, the brand's prospects in attitudinal space are high, especially when compared with its

**Table 8** Diagnostics for the Two Top Brands in Each Category, $T = 84$

| | SA | | | SB | | | WA | | | WB | | | JA | | | JB | | | CA | | | CB | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Awareness* | | | | | | | | | | | | | | | | | | | | | | | | |
| | SA | | | SB | | | WA | | | WB | | | JA | | | JB | | | CA | | | CB | | |
| Potential (%) = | 73 | | | 75 | | | 79 | | | 64 | | | 84 | | | 62 | | | 64 | | | 86 | | |
| Stickiness = | 0.35 | | | 0.33 | | | 0.48 | | | 0.48 | | | 0.56 | | | 0.57 | | | 0.30 | | | 0.30 | | |
| 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* | 0.030 | 0.059 | 0.611 | **0.091** | 0.010 | 0.000 | 0.052 | 0.048 | 0.278 | 0.072 | 0.039 | 0.062 | 0.048 | 0.036 | 0.179 | 0.031 | 0.036 | 0.390 | **0.030** | 0.008 | 0.000 | −0.001 | 0.034 | 0.978 |
| *Consideration* | | | | | | | | | | | | | | | | | | | | | | | | |
| | SA | | | SB | | | WA | | | WB | | | JA | | | JB | | | CA | | | CB | | |
| Potential (%) = | 83 | | | 71 | | | 50 | | | 70 | | | 69 | | | 81 | | | 73 | | | 80 | | |
| Stickiness = | 0.16 | | | 0.16 | | | 0.24 | | | 0.24 | | | 0.27 | | | 0.27 | | | 0.03 | | | 0.03 | | |
| 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* | **0.198** | 0.089 | 0.027 | **0.288** | 0.010 | 0.000 | 0.001 | 0.068 | 0.988 | **0.065** | 0.013 | 0.000 | **0.214** | 0.063 | 0.001 | **0.192** | 0.063 | 0.002 | **0.187** | 0.006 | 0.000 | **0.136** | 0.051 | 0.008 |
| *Liking* | | | | | | | | | | | | | | | | | | | | | | | | |
| | SA | | | SB | | | WA | | | WB | | | JA | | | JB | | | CA | | | CB | | |
| Potential (%) = | 29 | | | 11 | | | 2 | | | 22 | | | 9 | | | 27 | | | 26 | | | 24 | | |
| Stickiness = | 0.14 | | | 0.14 | | | 0.25 | | | 0.25 | | | 0.36 | | | 0.36 | | | 0.09 | | | 0.09 | | |
| 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* | **0.756** | 0.286 | 0.001 | **0.758** | 0.082 | 0.000 | 0.254 | 0.215 | 0.236 | **0.251** | 0.047 | 0.000 | **0.458** | 0.213 | 0.032 | **0.457** | 0.213 | 0.032 | **0.467** | 0.028 | 0.000 | **0.456** | 0.162 | 0.005 |

*Note.* Bold indicates statistically significant effects at $p < 0.05$.

competitor, shampoo brand SB. 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. 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 major shifts in their marketing allocations after $T = 84$. Shampoo brand SA increased its advertising spending by 50% and kept its prices the same. In contrast, water brand WA cut its advertising spend by 42% while also keeping prices the same. What are the consequences of these brands' strategic actions? We make directional sales forecasts up to 12 months later, based on their attitude criteria shown in Table 8. 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. The awareness metric has an ample potential of 73%, whereas the liking metric has a potential of 29%. Finally, liking converts to sales resulting in a forecasted increase in sales, which we denote with a "↑" in Table 9.

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 9, we offer model-based recommendations on changes in marketing mix decisions for advertising, i.e., increasing ("↑"), decreasing ("↓"), or maintaining ("−−") with a view to increasing brand sales. As Table 9 shows, brands that followed a *different* course from the model-based recommendations on marketing mix decisions (as depicted in the column "Agreement with model-based recommendation on spend") performed *worse* in terms of actual sales outcomes compared with brands that followed a course consistent with model-based recommendations. Thus, diagnosing attitudinal brand metrics can help directionally predict the impact of different marketing mix decisions on sales.

**Resource Allocation Implications**

We explore two additional ways in which our results are helpful for guiding marketing decision making. First, at any point in time, a manager can gauge the overall attractiveness of investing in marketing actions that move the needle on different attitudinal metrics. As an illustration, consider the diagnostics (at time = 84) for shampoo brand SA versus juice brand JB (in Table 8). Brand SA can make progress in its liking through advertising, which affects its preference score; this, in turn, converts into higher sales. By contrast, brand JB needs to use promotions to increase consideration that converts into sales. Numerous comparative scenarios can be derived from Table 9, but these are limited to top-line inferences; i.e., there are no cost and profit implications of these scenarios.

Second, we conduct a more formal analysis of optimal marketing mix spending using dynamic programming. To illustrate how to make marketing mix decisions by taking into account a mind-set metric, we pick two different shampoo brands, SC and SD, as they have similar sales levels but varying levels of awareness; shampoo brand SC has higher awareness than brand SD. We assume that both brands have the same 10% growth targets in terms of sales and awareness over the last 12 periods. Our goal is to obtain the optimal marketing mix path for both brands and validate our results using out-of-sample data from $t = 85$ to $t = 96$.

We address the optimal marketing path by considering two main steps (Gupta and Steenburgh 2008). In step 1, we estimate sales response and attitude response (awareness) models using time-series econometrics. In step 2, we find the optimal marketing path by using the estimated parameters in the optimization part. Specifically, we follow a DP approach used for solving multistage optimization problems (Rust 2006). The central idea of the DP is to maximize (minimize) the sum of today's reward (loss) and the discounted expected reward (loss) from the future periods (Bellman 1957). The details of these two steps are described in Web Appendix B.

**Table 9** **Illustrations of Model-Based Marketing Recommendations and Sales Outcomes**

| | Advertising spend | | | Sales outcome | |
|---|---|---|---|---|---|
| Brand | Recommend | Actual | Agreement with model-based recommendations on spend | Forecast conditional on agreement with recommendation | Actual |
| SA | ↑ | ↑ | Yes | ↑ | ↑ |
| SB | ↓ | ↓ | Yes | ↑ | −− |
| WA | ↑ | −− | No | ↑ | ↓ |
| WB | ↑ | −− | No | ↑ | ↓ |

*Note.* ↑ denotes an increase, ↓ denotes a decrease, and −− denotes no change.

**Figure 2 Optimal Price and Advertising Policies for Brands SC and SD**

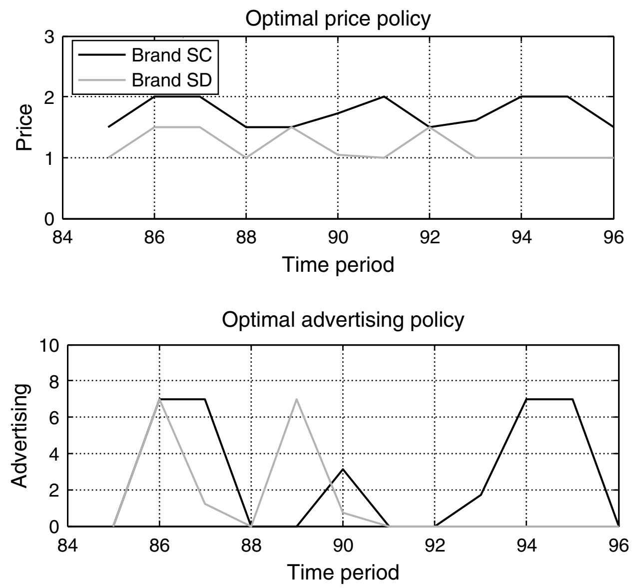
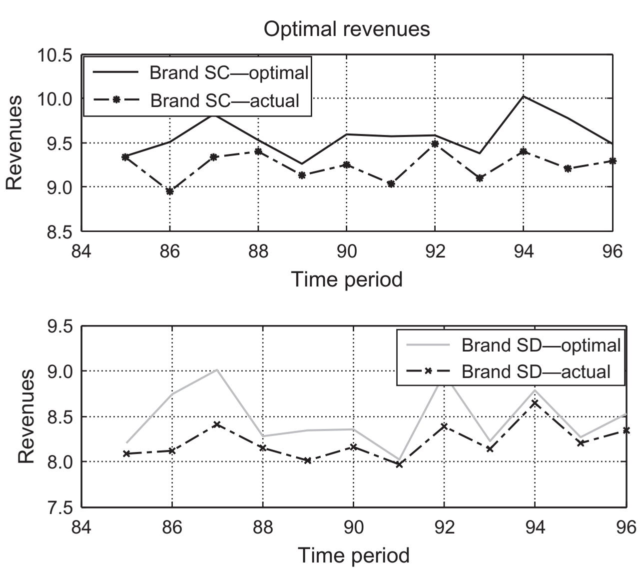



Figure 2 displays the optimal marketing mix path over 12 periods to achieve the targeted sales (+10%) and targeted awareness (+10%). In addition, we compute $(X^*_{p,t} \times S_t - X^*_{a,t})$, where $t$ is the time index; $X^*_p$ and $X^*_a$ are the optimal price and advertising policies, respectively; and $S$ is the observed sales level. The cost of increasing revenue performance is through increased advertising or lowering price, or both. Note that despite the similar sales starting position and target, our model recommends different marketing policies for each brand.

Figure 3 shows the optimum sales revenues achieved upon implementing the optimal price and advertising actions from $t = 85$ to $t = 96$. Both brands substantially increase projected sales revenues: 40% for brand SC and 34% for brand SD.

**Figure 3 Optimal Revenues for Brands SC and SD**




## 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 chief marketing officer also needs to understand the *consumer behavior reasons* why marketing does or does not affect 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. Table 10 provides an overview of four corner cases. The estimates reported in Table 8 allow a classification of the brands into the four cells.

First, if a brand has low sales conversion from consumer attitudinal metrics, and low responsiveness to marketing, we label that scenario a *transactions effect at best*. For the eight brands with three attitudinal metrics in Table 8, only one can be classified into this cell. Thus, for most brands, marketing mix strategies result in sales conversion through the "mind-set 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

**Table 10 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 |

that scenario an *ineffective marketing focus*. For example, brands that invest substantially in consideration set-enhancing advertising may fail to see a substantial sales lift. A case in point is water brand WA with respect to advertising. Increases in advertising generate awareness and consideration lifts that do not convert to sales. Hence, for water brand WA, advertising represents an ineffective marketing focus that may please managers focused on awareness and consideration metrics but not managers focused on increasing the top line.

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 advertising. Consideration and liking have high sales conversion for SB, but they do not respond well to marketing spending. Managers can use such insights to motivate a detailed analysis of the reasons, which may include the wrong message, the wrong execution, the wrong communication channel, the wrong timing, etc. In contrast, increases in shampoo brand SA's advertising generate liking that converts into sales. Hence, advertising is an "effective marketing lever" for shampoo brand SA to generate sales conversion from a lift to liking.

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, cereal brand CA has sales conversion from awareness and consideration, which have 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 consideration and eventually to a 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, with an assessment of the relative performance of log-log models, log-linear models, as well as other forms of nonlinearity. Moreover, the effectiveness of marketing actions (e.g., promotions and advertising) could be modeled as functions of awareness, consideration, and liking. In addition, we model potential as the remaining distance to the maximum for its ease of elasticity definition, but future research should compare alternative operationalizations (e.g., square root of the remaining distance to the maximum) 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 observations at different time intervals (e.g., weekly, monthly, quarterly) and including data on 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. Degree of differentiation and other factors such as market share may be important drivers of the cross-brand differences in mind-set metric criteria. A company interested in brand equity may, in addition, want to examine to which extent its brand can command a revenue premium compared with other brands and private labels (Ailawadi et al. 2003). The revenue premium can itself be modeled as a function of mind-set metrics. Moreover, data on the profits gained from better decisions would enable managers to weigh them against the cost of collecting attitudinal metrics, thus providing a return on investment measure for such data.

If individual-level attitude metrics are available, these could be used in more granular response model specifications. Indeed, the lack of attitudinal metrics that match the transactional records is a limitation of our approach. Attitudinal tracking data are typically survey based, which is costly and subject to sampling error. 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 media, social network sites, blogs, product reviews, and similar online word-of-mouth forums. Some preliminary evidence suggests that "Internet-derived consumer opinions" are predictive of subsequent behavior (e.g., Shin et al. 2013). Future research should examine which Internet-derived attitudinal metrics are the most relevant and investigate the extent to which measurement error in online versus off-line metrics may matter. These metrics could then be substituted for the survey-based measures that were used in this paper.

## Supplemental Material

Supplemental material to this paper is available at http://dx.doi.org/10.1287/mksc.2013.0841.

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