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Demonstrations of marketing effectiveness currently proceed along two parallel tracks: Quantitative researchers model the direct sales effects of the marketing mix, and advertising and branding experts trace customer mind-set metrics (e.g., awareness, affect). The authors merge the two tracks and analyze the added explanatory value of including customer mind-set metrics in a sales response model that already accounts for short- and long-term effects of advertising, price, distribution, and promotion. Vector autoregressive modeling of the metrics for more than 60 brands of four consumer goods shows that advertising awareness, brand consideration, and brand liking account for almost one-third of explained sales variance. Competitive and own mind-set metrics make a similar contribution. Wear-in times reveal that mind-set metrics can be used as advance warning signals that allow enough time for managerial action before market performance itself is affected. Specific marketing actions affect specific mind-set metrics, with the strongest overall impact for distribution. The findings suggest that modelers should include mind-set metrics in sales response models and branding experts should include competition in their tracking research.

Keywords: customer mind-set metrics, market response models, time-series models, vector autoregressive models, forecast error variance decomposition, leading indicators

Mind-Set Metrics in Market Response Models: An Integrative Approach

> How do you know if you are doing a good job for the customer? It is not shown in your profits this year but in your share of the customer's mind and heart. Companies that make steady gains in mind share and heart share will inevitably make gains in market share and profitability. (Kotler 2003, pp. 38–39)

The call for marketing accountability has been growing over the past decade, and answering this call is considered key to regaining marketing's standing in the C-suite (chief executive officers, chief financial officers, chief marketing officers, chief information officers, and so forth; see Webster, Malter, and Ganesan 2003). As a result, marketers have shown a vivid interest in metrics, as evidenced by a series of recent books on the topic (e.g., Davis 2006; Farris et al. 2006; Lehmann and Reibstein 2006). Most metrics-based quantitative research has focused on linking marketing actions directly to the company's top line, bottom line, and stock market performance (Lehmann 2004; Pauwels et al. 2004; Srinivasan and Hanssens 2009). However, there are also recent calls to complement these input and output measures with throughput measures of consumers' perceptions, attitudes, and intentions. For example, Gupta and Zeithaml (2006, p. 734) call for research that "incorporates perceptual constructs in behavioral outcome models," and the Marketing Science Institute (2006) includes the combining of behavioral and attitudinal data to predict brand performance among its 2006–2008 research priorities.

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We refer to measures of consumers' perceptions, attitudes, and intentions as "mind-set metrics." They are collected with surveys, often on a regular basis. Mind-set metrics are not particularly popular among quantitative modelers. For example, Gupta and Zeithaml (2006, p. 721) observe that "researchers and companies find that they can bypass unobserved metrics." When quantitative modelers establish the short-term and long-term sales and profit effects of the marketing mix (e.g., Hanssens, Parsons, and Schultz 2001), they typically treat the customer's mind and heart as a "black box." In contrast, mind-set metrics are often used by advertising and branding experts and by researchers in consumer behavior who examine the influence of marketing actions on the consumer mind-set. These experts and researchers typically do not examine the ultimate effect on sales and ignore the impact of competitive actions.

The main research question here is the following: Does including mind-set metrics add explanatory power to a sales response model that already includes marketing-mix actions? If the answer is yes, the subsequent research questions are how large the effects of mind-set metrics on sales are and how large the effects of marketing actions on the mind-set metrics are. In addition, it is helpful for managers to know whether mind-set metrics can be used as advance warning signals. Therefore, the final research questions are what the wear-in times of mind-set metric changes on sales are and how they compare with the wear-in times of marketing-mix action changes on sales. To answer these research questions, we proceed as follows: We first provide the research framework, followed by a description of the data set with comprehensive information on performance metrics, marketing-mix metrics, and mind-set metrics for more than 60 brands in four fast-moving consumer goods categories on a four-weekly basis during a period of seven years. Next, we describe the estimation methodology of vector autoregressive (VARX) models with exogenous variables, which enables us to address endogeneity by incorporating lagged effects and complex feedback loops that are typical with this type of data (Dekimpe and Hanssens 2007). We then present the empirical findings on integrating mind-set metrics into market response models. Finally, we conclude with the limitations of the study and directions for further research.

RESEARCH FRAMEWORK

Mind-set metrics have a long history in marketing, especially in the advertising world. Russell Colley's (1961) work has influenced the advertising planning process by focusing advertisers' attention on communication-based measures, which correspond to our mind-set metrics, instead of sales-based objectives. Mind-set metrics are also the building blocks of the hierarchy-of-effects model of advertising (Palda 1966; Vakratsas and Ambler 1999). The central idea of this model is that each advertisement exposure moves the consumer forward through a hierarchical sequence of events, including cognition (e.g., awareness, knowledge), affect (e.g., liking, desire), and, ultimately, behavior (purchase, sometimes measured as purchase intention). More recently, mind-set metrics and the idea of this hierarchical sequence have also been used in the evaluation of brand performance from a customer's perspective. In using mind-set metrics to track brand performance, brand experts examine not just the effect of advertising but also that of the entire marketing mix. For example, Keller and Lehmann (2006) propose five aspects of customer-based brand equity measurement: awareness, association, attitude, attachment, and action.

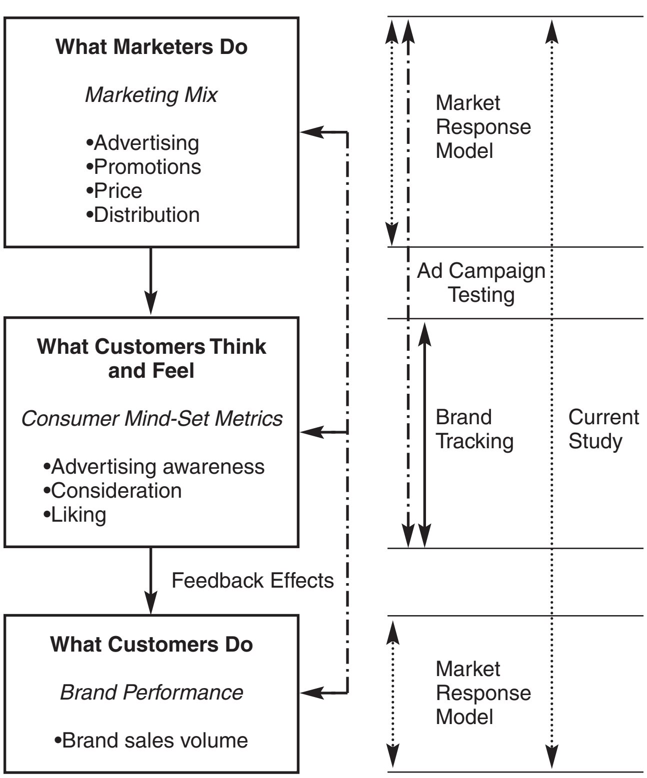
However, mind-set metrics are also controversial. Palda (1966, p. 23) was probably the first to express his concerns when he wondered if collecting intermediate measures was really worth the trouble: "Is it, on balance, really more difficult and expensive to investigate the direct link between advertising expenditure and sales, than it is to undertake research into each step of the hierarchy…?" Likewise, Boyd, Ray, and Strong (1972) argue that if communication metrics are ultimately predictive of sales, which they should be, sales should be measured directly instead. Even today, mind-set metrics remain associated mostly with an advertising world that does not want to be held accountable for sales, based on the argument that sales response models capture only short-term effects and miss the long-term sales benefits of brand building.

Conversely, advocates of mind-set metrics have hailed them as early signals of brands' performance successes and problems (Ambler 2003; Pauwels and Joshi 2008). Their main argument is that if marketing actions move customers closer to the buying decision in a series of mental steps, tracking and interpreting the corresponding mind-set metrics will provide early evaluation signals (LaPointe 2005). Specific actions that strengthen the competitive position of the brand in customers "hearts and minds" may not translate into sales immediately, but mind-set metrics can verify that marketing moves customers in the right direction (Keller and Lehmann 2006). In the case of performance problems, the consumer may not react immediately by switching to another brand, but mind-set metrics may diagnose a declined interest and offer a chance for remedial action before the bottom line is affected. In addition, it may be difficult to convince consumers to switch back, and it may be easier instead to intervene before they actually leave for greener pastures.

Previously, we referred to several calls for the integration of input, throughput, and output metrics in sales models. Figure 1 summarizes our research framework in visual form. Note that, conceptually, no purchase can occur without the consumer's mind being involved. Therefore, continuous individual consumer tracking of all relevant mind-set metrics should capture all marketing effects. In practice, however, mind-set metrics cannot catch the full dimensionality and scope of the complex consumer mind-set. Therefore, an empirical model may pick up sales effects of marketing actions that do not (yet) register in changes to the observed set of mind-set metrics.

As evident from Figure 1, no extant method comprehensively incorporates all these metrics simultaneously in assessing sales response. Advertising campaign tests typically consider only what marketers do and what customers think and feel (Belch and Belch 2004). Studies that track brand health typically pay attention only to what customers think and feel (Keller 2003). Market response models typically address only the first and third box in Figure 1, focusing on what marketers and customers do (e.g., Hanssens, Parsons, and Schultz 2001). The objective of this study is to examine whether practice should combine all three groups of metrics into an integrative modeling framework.

Figure 1
FRAMEWORK: MARKETING ACTIONS, CUSTOMER MIND-SET METRICS, AND BRAND PERFORMANCE



We do not formulate hypotheses on the exact nature of the relationships among the mind-set metrics themselves.[1] The VARX models we use for the analysis allow for "multiple hierarchies" and the idea that the impact of a marketing action on the customer mind-set is neither immediate nor simultaneous but occurs in "situationally varying and complex patterns of temporal precedence" (Batra and Vanhonacker 1988, p. 24). Indeed, both prior brand experience and marketing actions such as advertising can be expected to build connections in consumers' memories, resulting in subsequent purchase behavior over time. Therefore, our framework allows for feedback effects of brand performance on the consumer mind-set and on the firms' marketing decisions. In addition, the flexible nature of the econometric specification enables us to uncover new insights into the wear-in and wear-out time.

DATA

We use French data from Prométhée, a brand performance tracker developed by Kantar Worldpanel, which reports the metrics in which we are interested for four-weekly periods. Prométhée presents a comprehensive, state-of-the-art brand dashboard, with the marketing mix, mind-set metrics, and performance metrics. Its key features include a synchronized data collection process and an identical definition of which products belong to each brand across data sources. The details on the four data sources that Kantar Worldpanel integrates are as follows:

1. A nationally representative panel of households is surveyed weekly on aided brand awareness, aided advertising awareness, liking, inclusion in the consideration set, and purchase intentions at the brand level in a given product category. For each product category, more than 8000 surveys are collected each year, but any given household is interviewed at most twice per year. Prométhée reports four-week averages of the weekly responses for each indicator.
2. A nationally representative household panel with 12,000 members is used to measure purchases and prices paid. To avoid mere measurement biases (Morwitz, Johnson, and Schmittlein 1993), this panel is different from the survey panel. The use of a household panel for purchases and prices paid ensures complete coverage of all retail chains in this market, including hard discounters. Households use a handheld scanner to scan each UPC (Universal Product Code) and manually enter the price paid from the receipt. Based on the UPC, Worldpanel determines the volume or weight purchased to aggregate across different products and package sizes to determine brand sales volume. Therefore, the price is a price per volume or weight unit.
3. A panel of 500 distribution points is used to track distribution presence and promotional actions. Store presence is determined for each UPC. A value-weighted overall distribution presence is then calculated at the brand level in the form of a percentage. Stores are weighted for their sales in the product category, and each UPC is weighted for its contribution to sales. Promotion is measured as the average percentage of value-weighted distribution that is on promotion for a given observation period. The following forms of promotion are registered: in-store communication, presence of in-store flyers, price promotions, and bonus buys.
4. To measure advertising support, two sources are combined. Some media agencies transmit the expenses directly to Kantar Worldpanel (e.g., for billboards). For media that are not covered with this method (e.g., television), all advertisements are identified. Media space prices are publicly available, which then enables Kantar Worldpanel to convert the number of advertisements and their duration to communication expenses. These expenses are aggregated across four weeks, based on the date of the advertisement (television) or the date of the media support availability (press).

For the period between January 1999 and May 2006, we have a complete set of observations on 74 brands from four categories, differing on the food versus nonfood dimension and in terms of storability: breakfast cereals (21 brands), bottled water (18 brands), fruit juice (17 brands), and shampoo (18 brands). The data frequency is four weeks, amounting to 96 observations per brand per measure. As a focal brand performance measure, we use sales volume aggregated across all product forms of each brand (in milliliters for shampoo, water, and fruit juice and grams for cereal), but we also verify the robustness of the results by replicating the analysis with market share and revenues.[2] For the

[1]Research on the hierarchy of effects shows that evidence on the exact sequence of effects is mixed (Franses and Vriens 2004; Vakratsas and Ambler 1999; Zinkhan and Fornell 1989; Zufryden 1996). A likely explanation is that the sequence depends on several product category and consumer factors that vary across studies (Batra and Vanhonacker 1988). Therefore, we decided to adopt a modeling approach that does not impose a sequence of effects but instead is able to capture multiple interactions among our measures, including the mind-set measures.

[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 article.

marketing mix, the 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 consumer mind-set metrics: advertising awareness, brand liking, and inclusion in the consideration set. This selection aimed to cover the three main stages of the hierarchy of effects: cognition, affect, and conation. Aided brand awareness, another available measure, showed too little variation due to ceiling effects, and purchase intention was too closely correlated with consideration set.

For advertising awareness, using a list of all brands present on the market, survey respondents indicated those for which they "remember having seen or heard advertising in the past two months." This measure gives the percentage of respondents who were aware. Liking is measured on a five-point scale ("like enormously," "a lot," "a little," "not really," "not at all"), and the measure we use is the average rating. For the consideration set, using a list of all brands on the market, respondents indicated "the brands that you would consider buying." We use the percentage of respondents who consider buying as the measure. We also include competitive prices, distribution, promotion, and advertising operationalized as the market-share-weighted prices, distribution, promotion, and advertising of the other brands (other than the focal brand) in the category, as Dekimpe and Hanssens (1999) and Slotegraaf and Pauwels (2008) recommend.[3]

Overall, this data set, with a temporal duration of more than seven years, a presence of different players with different strategies in different product categories, and wide coverage of both the marketing mix and consumer mind-set metrics, is uniquely suited to address the research questions on the impact of mind-set metrics on brand performance. From a measurement perspective, another important feature is that all four data sources use an identical definition of the observation periods and the brands. Table 1 provides descriptive statistics on the data, and Figure 2 plots, for each mind-set metric, the brand with the median amount of variation on that metric. At the individual brand level, we observe sufficient variation in each mind-set metric over time to relate it to both marketing actions and brand sales. This benefit likely results from both the long time span of the data (seven years versus the standard three years) and the four-weekly (versus weekly) data interval.

[3]We follow Pauwels, Hanssens, and Siddarth (2002) in adopting static weights (i.e., average share across the sample) rather than dynamic (current-period) weights to compute the weighted prices.

Table 1
DESCRIPTIVE STATISTICS ON MARKETING-MIX AND MIND-SET METRICS

Variables	*Cereals*	*Bottled Water*	*Fruit Juice*	*Shampoo*
Distribution	95.0	91.2	79.6	92.4
(value-weighted %)	(18.5)	(8.0)	(13.1)	(15.6)
Promotions	15.1	16.8	21.9	24.0
(% of volume on promotion)	(3.7)	(3.7)	(2.8)	(4.7)
Advertising	251.6	402.1	121.9	359.0
(in thousands of euros)	(179.5)	(343.3)	(119.1)	(247.0)
Advertising awareness	16.9	20.6	11.4	18.5
(% aware)	(3.0)	(1.5)	(3.3)	(3.1)
Consideration	18.4	17.9	18.3	15.9
(% considering buying)	(2.7)	(.8)	(3.1)	(2.3)
Liking	5.1	5.3	5.6	4.6
(scale value)	(1.0)	(.5)	(.8)	(1.0)

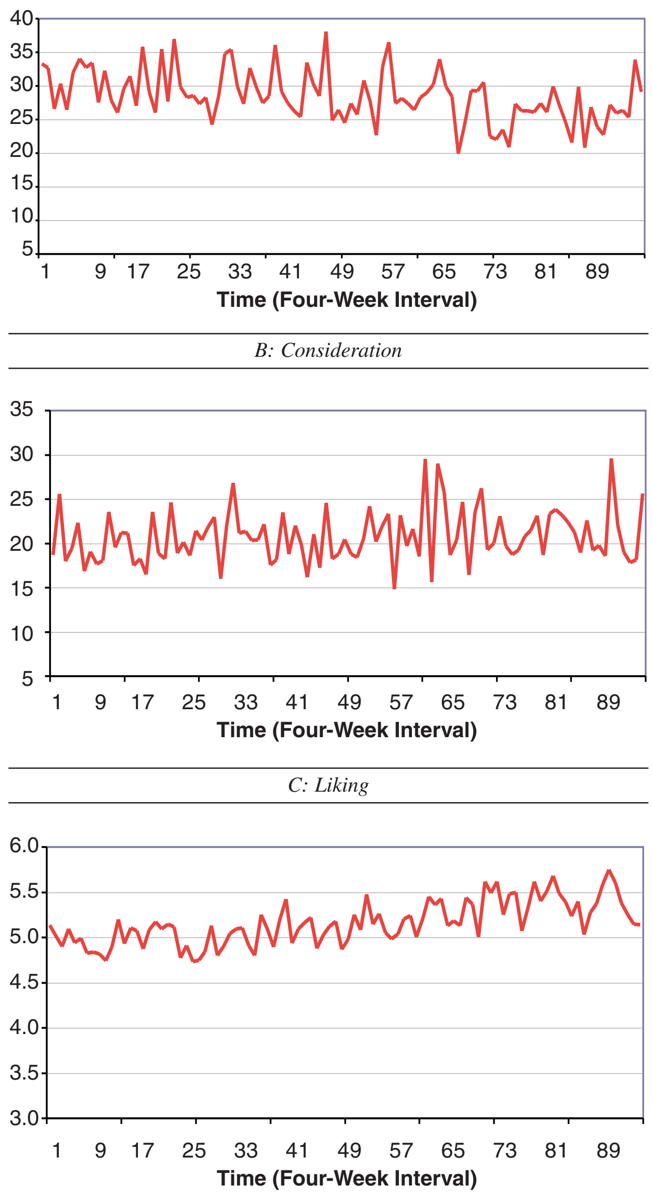
Notes: Average values for four weeks across all brands with intertemporal standard deviations in parentheses.

Figure 2
MIND-SET METRICS FOR REPRESENTATIVE BRANDS

A: Awareness

B: Consideration

C: Liking



Notes: For each mind-set metric, we display the brand with the median variation on that metric.

MIND-SET METRICS IN MARKET RESPONSE MODELS: RESEARCH METHODOLOGY

The dynamic interactions and feedback effects in Figure 1 are captured in VARX models (Dekimpe and Hanssens 2007). First, the endogenous treatment of marketing actions implies that they are explained by both past marketing actions and past performance variables. Second, VARX models are able to capture complex feedback loops that may affect brand performance over time. For example, an increase in advertising in a given week may generate a high level of advertising awareness, inducing some consumers to consider the brand and try it, after which they develop brand liking. Their subsequent purchases may increase not only brand sales but also consideration by their family, friends, and colleagues who see them use the brand. Because of such chains of events, the full performance implications of the advertising may extend well beyond the immediate effects. By capturing these feedback loops, VARX estimation yields a comprehensive picture of the full dynamic system, including marketing actions, mind-set metrics, and sales performance.

The empirical time-series analysis proceeds in two steps that are applied to each brand separately. First, we estimate the dynamic interactions among sales, advertising awareness, brand consideration, brand liking, the marketing mix (price, promotions, distribution, and advertising), and the corresponding competitive mind-set and marketing-mix metrics using VARX models.[4] Second, we use generalized forecast error variance decomposition (GFEVD) and generalized impulse response functions (GIRF) to quantify the relative influence of marketing actions versus the consumer mind-set measures on sales. Finally, we quantify the extent to which marketing-mix actions drive the mind-set metrics. Table 2 provides references that detail each step.

Step 1: VARX Model Specification

We estimate a 15-equation VARX model per brand, in which the endogenous variables are sales, the three mind-set variables (advertising awareness, brand consideration, and brand liking), four marketing-mix variables (average retail price, advertising, distribution, and promotion), and the seven corresponding competitive variables. In matrix notation, we write the model as follows:

$$(1)\qquad Y_t = A + \sum_{i=1}^{p} \Phi_i Y_{t-i} + \Psi X_t + \Sigma_t,\ t = 1, 2, \ldots, T,$$

where A is a 15×1 vector of intercepts, Y_t is a 15×1 vector of the endogenous variables, X_t is a vector of exogenous control variables—(1) a deterministic-trend t to capture the impact of omitted, gradually changing variables and (2) quarterly dummy variables to account for seasonal fluctuations in sales or any other endogenous variable—and Σ_t is the covariance matrix of the residuals. Subscript i denotes the brand and p is the number of the lags in the model. For the benchmark models, we estimate the nine-equation benchmark VARX model obtained by deleting the six mind-set metric equations from the full VARX model and the seven-equation VARX model obtained by deleting the eight marketing-mix equations from the full VARX model. We provide the details of these models, including details on the parameter-to-observation ratios in Technical Web Appendix A (http://www.marketingpower.com/jmraug10).

Step 2a: GFEVD

The VARX estimation is only the first step needed to answer the research questions. From the VARX parameters, we derive GFEVD estimates to investigate whether, and to what extent, mind-set metrics explain brand sales performance beyond the impact of marketing-mix actions. The GFEVD approach quantifies the dynamic explanatory value on sales of each endogenous variable. Akin to a "dynamic R-square," GFEVD provides a measure of the relative impact over time of shocks initiated by each of the individual endogenous variables in a VARX model, without the need for the researcher to specify a causal ordering among these variables (Nijs, Srinivasan, and Pauwels 2007; Pesaran and Shin 1998). We derive GFEVD estimates using the following equation:

[4]VARX model specification requires a test on the statonarity of each endogenous variable. We use the augmented Dickey–Fuller test to verify the presence of unit roots in the data, applying the iterative procedure proposed by Enders (2004, pp. 181–83) to decide whether to include a deterministic trend in the test. When the test confirms the existence of a unit root, we treat the variable as evolving. When more than one variable in a VARX system is found to be evolving, we implement Johansen's cointegration test to capture a possible long-term equilibrium among the evolving variables (Dekimpe and Hanssens 1999; Srinivasan, Popkowski, and Bass 2000).

Table 2

OVERVIEW OF ANALYSIS STEPS

Methodology	*Econometrics Literature*	*Marketing Literature*	*Research Questions*
1a. Unit Root Tests			
Augmented Dickey–Fuller	Enders (2004)	Pauwels, Hanssens, and Siddarth (2002)	•Is each variable (mean/trend) stationary or evolving (unit root)?
Structural break test	Perron (1989) Perron (1990) Zivot and Andrews (1992)	Srinivasan, Popkowski, and Bass (2000)	•Is there a structural break in the time series of each variable?
1b. VARX	Lütkepohl (1993)	Dekimpe and Hanssens (1995) Nijs et al. (2001)	•How do key variables interact, accounting for exogenous factors?
2a. Variance Decomposition			
Forecast error variance decomposition	Enders (2004)	Hanssens (1998) Pauwels et al. (2004)	•Do mind-set metrics matter in explaining sales over time…?
GFEVD	Pesaran and Shin (1998)	Nijs, Srinivasan, and Pauwels (2007)	•…without imposing a causal ordering on the variables?
2b. Impulse Response Functions	Pesaran and Shin (1998)	Nijs et al. (2001) Srinivasan et al. (2004)	•What is the net performance response of a marketing impulse?

$$\theta_{ij}^{g}(n) = \frac{\sum_{l=0}^{n}\left[\psi_{ij}^{g}(l)\right]^2}{\sum_{l=0}^{n}\sum_{j=0}^{m}\left[\psi_{ij}^{g}(l)\right]^2}, \text{ i, j} = 1, ..., m,$$

where ψ_{ij}^{g} is the value of a GIRF following a one-unit shock to variable i on variable j at time l (Pesaran and Shin 1998).[5] Importantly, the GFEVD attributes 100% of the forecast error variance in sales to either (1) the past values of the other endogenous variables or (2) the past of sales itself, also known as "purchase inertia."[6] The former (e.g., a past change in advertising awareness drives current sales) is much more managerially and conceptually interesting than the latter (a past change in sales drives current sales, but we do not know what induced that past change in sales). Therefore, we assess the dynamic explanatory value of the mind-set metrics by the extent to which they increase the sales forecast error variance explained by the potential drivers of sales (i.e., other endogenous variables) in the model and thus reduce the percentage explained by past sales.

The relative importance of the drivers is established with the GFEVD values at six months, which reduces sensitivity to short-term fluctuations.[7] To establish the statistical significance of the GFEVD estimate (at the $p < .05$ level), we obtain standard errors using Monte Carlo simulations (see Benkwitz, Lütkepohl, and Wolters 2001). Although GFEVD is the appropriate method to assess the main research question, it comes at a cost: It only allows comparable analyses of brands with stationary sales volumes (84% in the data set). Stationarity implies that even though a shock to sales can cause large fluctuations (variance) over time, its effect ultimately dies out, and the sales series reverts back to its deterministic (mean + trend + seasonality) pattern. The variance of such stationary sales series is finite and time invariant. In contrast, the variance of an evolving sales volume series (implying that shocks have permanent effects) is time dependent and theoretically (as t approaches infinity) infinite (Pesaran and Shin 1998; Srinivasan, Pauwels, and Nijs 2008).

We apply GFEVD for (1) the full VARX model in Equation 1, (2) the restricted VARX model that omits the mind-set metrics and thus corresponds to the typical VARX models estimated in previous marketing literature, and (3) the restricted model that omits the marketing-mix variables. A comparison of the GFEVD results across these models enables us to assess whether mind-set metrics (marketing-mix variables) yield additional explanatory power in a model that already accounts for long-term effects of marketing-mix variables (mind-set metrics) on sales performance and their dynamic interactions.

Step 2b: GIRF

We examine the remaining questions by inspecting the GIRF using the estimated parameters of the full VARX model. From all these parameters, the impulse response function estimates the net result of a "shock" to a marketing variable on the performance variables relative to their baselines (their expected values in the absence of the marketing shock). Specifically, we measure the long-term performance (brand sales) response to a one-unit shock (Pauwels, Hanssens, and Siddarth 2002; Nijs et al. 2001; Srinivasan et al. 2004). We estimate GIRFs with the simultaneous-shocking approach (Dekimpe and Hanssens 1999; Evans and Wells 1983), in which the information in the residual variance–covariance matrix of Equation 1 is used to derive a vector of expected instantaneous shock values. The advantage of this approach is that it does not require selecting a temporal ordering among the variables of interest. We subsequently derive standard errors using the Monte Carlo simulation approach with 250 runs in each case (see Horváth 2003) to establish the statistical significance of the parameters (at the $p < .05$ level).

We derive the following three summary statistics from each GIRF: (1) the immediate performance impact on brand sales, which is readily observable to managers and therefore may receive considerable managerial scrutiny; (2) the permanent impact (i.e., the value to which the impulse response function converges); and (3) the total or cumulative impact, which combines the immediate effect with all effects across the dust-settling period. In the absence of permanent effects, this total impact becomes the relevant metric to evaluate performance outcomes (Pauwels, Hanssens, and Siddarth 2002; Pauwels and Srinivasan 2004). Finally, we obtain the wear-in time of each driver's effect on sales as the period with the highest (in absolute value) impulse response coefficient (Pauwels and Hanssens 2007). Although VARX models, GFEVD, and GIRFs have recently been introduced to the marketing literature (e.g., Bronnenberg, Mahajan, and Vanhonacker 2000; Nijs et al. 2001; Nijs, Srinivasan, and Pauwels 2007), to the best of our knowledge, ours is the first study to use them to measure the contribution of mind-set metrics to brand performance.

FINDINGS

The unit root tests classify 62 of the 74 performance series as stationary. As we explained in the previous section, we focus on these 62 brands (84% of all brands) in the analysis. To report the findings, we averaged results across all brands or across all brands of each category.

Mind-Set Metrics Matter in Market Response Models

For both the full model in Equation 1 and the restricted benchmark models without mind-set metrics and marketing-mix actions, we report in Table 3 their GFEVD results. In the benchmark model with only marketing-mix variables, own and competitive marketing mix account for 26.3% and

[5]In GFEVD, an initial shock is allowed to (but does not need to, depending on the size of the corresponding residual correlation) affect all other endogenous variables instantaneously. Nijs, Srinivasan, and Pauwels (2007) recently applied this in a marketing setting.

[6]Purchase inertia means that sales gains now result in sales gains later. We can also interpret this as "behavioral loyalty": Consumers tend to repeat past buying decisions. Purchase inertia may occur through several mechanisms, including feedback from purchases to mind-set metrics (e.g., consumers who buy the product like it and then repurchase it) and from purchases to marketing actions (e.g., a purchase increase allows the brand manager to spend more on promoting the brand, which in turn increases purchases). Note that purchase inertia is unrelated to the unexplained residuals. Our model explains the endogenous variable "sales" by its own past and the past of the other endogenous variables. An analogy is the "past purchase loyalty" in Guadagni and Little's (1983) model: This variable explains a substantial part of choice and is not related to the model's unexplained residuals.

[7]Previous studies have shown that a period of 26 weeks (6 months) is sufficient for stationary series in consumer packaged goods to capture dynamic effects (Pauwels and Srinivasan 2004; Srinivasan et al. 2004).

Table 3

VARIANCE EXPLAINED BY DYNAMIC DRIVERS OF BRAND PERFORMANCE BASED ON GFEVD ANALYSIS

	Brand Sales Performance									*Share*	*Revenue*
	M			*Mdn*			*SD*			*M*	
Response to	*BM1*	*BM2*	*FM*	*BM1*	*BM2*	*FM*	*BM1*	*BM2*	*FM*	*FM*	*FM*
Own...											
Price	8.7%		7.6%	8.8%		7.5%	8.9%		7.7%	8.5%	4.9%
Promotion	10.3%		7.5%	10.2%		7.5%	8.2%		6.5%	8.0%	7.8%
Advertising	4.6%		4.4%	4.7%		4.3%	5.1%		4.3%	3.9%	4.5%
Distribution	2.7%		3.6%	2.8%		3.5%	2.7%		3.1%	3.8%	3.4%
Own Marketing Mix	26.3%		23.1%	26.5%		22.8%	7.3%		5.9%	24.2%	20.6%
Competitive...											
Price	3.2%		3.7%	3.1%		3.7%	2.9%		3.2%	2.5%	3.3%
Promotion	4.6%		4.0%	4.6%		4.1%	6.4%		5.0%	4.2%	4.1%
Advertising	3.4%		3.2%	3.5%		3.1%	2.6%		2.6%	2.5%	3.1%
Distribution	2.2%		2.9%	2.3%		3.1%	2.4%		3.2%	3.5%	2.8%
Competitive Marketing Mix	13.4%		13.8%	13.5%		14.0%	4.0%		3.6%	12.7%	13.3%
Own...											
Ad awareness		7.8%	3.4%		7.7%	3.3%		8.8%	3.2%	3.3%	3.3%
Consideration		4.4%	2.7%		4.6%	2.6%		6.3%	3.9%	2.6%	2.6%
Liking		3.1%	2.3%		3.2%	2.4%		3.1%	2.0%	1.9%	2.1%
Own Mind-Set		15.3%	8.4%		15.5%	8.3%		6.8%	3.2%	7.8%	8.0%
Competitive...											
Ad awareness		4.2%	2.6%		4.3%	2.7%		4.4%	2.5%	2.9%	3.4%
Consideration		3.1%	3.1%		3.2%	3.2%		3.4%	3.3%	2.6%	3.2%
Liking		3.1%	2.2%		3.0%	2.3%		3.2%	2.0%	1.8%	2.1%
Competitive Mind-Set		10.4%	7.9%		10.5%	8.2%		3.7%	2.7%	7.3%	8.7%
Purchase Inertia	60.3%	74.3%	46.8%	60.0%	74.0%	46.7%	12.3%	12.2%	12.6%	48.0%	49.4%

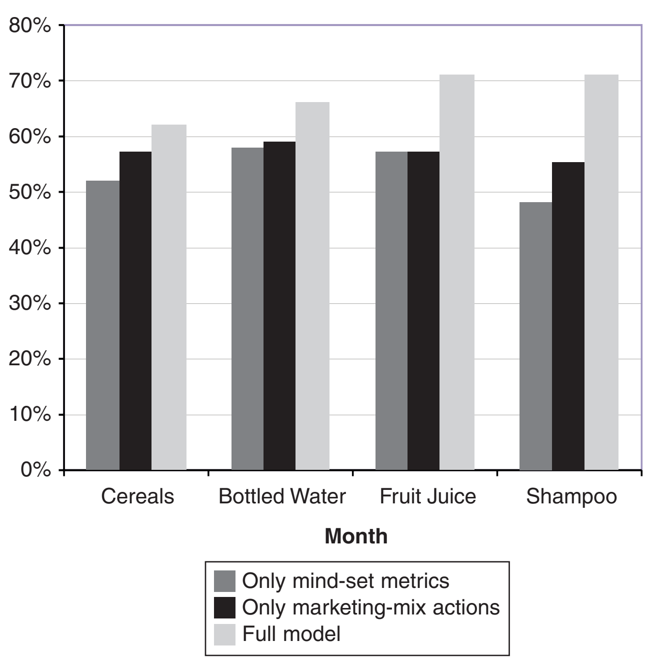
Notes: BM1: model with only marketing mix; BM2: model with only mind-set; and FM: full model.

13.4%, respectively, of the total variation in brand sales. The remaining 60.3% of the variation in brand sales is attributed to the own past of the sales series, also known as purchase inertia. The average (adjusted) R-square for brand sales is .57 (.53). In the benchmark model with only mind-set metrics, own and competitive mind-set metrics account for 15.3% and 10.4%, respectively, of the total variation in brand sales. The remaining 74.3% of the variation in brand sales is attributed to purchase inertia. The average (adjusted) R-square for brand sales is .54 (.50). The lower explained variance in this second benchmark model is consistent with our previous discussion of the practical limitations of mind-set metrics: Any set of metrics (including ours) is unlikely to fully capture all sales effects of marketing actions.[8] The brand-specific findings on the adjusted R-square for the estimated models appear in Web Appendix A (Tables A1, A2, and A3; see http://www.marketingpower.com/jmraug10). Figure 3 visualizes the explanatory power (R-square) for the benchmark model with mind-set metrics only, the benchmark model with marketing mix only, and the full model for each category.

Having established the better explanatory power of the full model, we use its GFEVD results to address the main research question. Own marketing actions account for 23.1%, and competitive marketing mix accounts for 13.8% of the variation in brand sales. The three consumer mind-set metrics together account for 8.4% of the variation, and competitive mind-set metrics account for an additional 7.9% of the variation in past sales. Thus, mind-set metrics—own and competitive—together account for 16.3% of the variation in brand sales. Therefore, the percentage of variation attributed to inertia goes down from 60.3% to 46.8% when mind-set metrics are accounted for in the model. Moreover,

Figure 3

COMPARISON OF R-SQUARE OF THE BENCHMARK MODELS VERSUS FULL MODEL



[8]Adding either brand awareness or purchase intention, or replacing an included mind-set metric with these variables, does not improve model fit.

the full model outperforms the restricted benchmark models in explaining brand sales with an average (adjusted) R-square of .67 (.61). Table 3 also points to the importance of competitive mind-set metrics, which contribute almost as much to sales variation as own mind-set metrics do (7.9% versus 8.4%). In contrast, competitive marketing-mix actions contribute only half as much as own marketing actions (23.1% versus 13.8%), consistent with the marketing-mix modeling literature (e.g., Van Heerde, Srinivasan, and Dekimpe 2010). Thus, it seems crucial to measure the share of minds and hearts of competitors together with one's own if mind-set metrics are used to explain performance. In summary, the answer to the first research question is yes, mind-set metrics help explain sales even in a model that accounts for long-term effects of own and competitive marketing-mix actions.

We also verified whether the findings generalize to performance metrics other than sales volume, and we ran robustness checks with brand market share and brand revenue (see the last two columns of Table 3). The results are remarkably similar, and we conclude that the finding on the contribution of mind-set metrics versus marketing mix in explaining brand performance does not depend on the performance metrics chosen.

Sales Response Elasticities of Consumer Mind-Set Metrics Versus Marketing-Mix Actions

Having established that both marketing-mix actions and mind-set metrics help explain sales, we examine whether there are general patterns in the response elasticities across brands.[9] Table 4 reports both immediate and total (i.e., cumulative) elasticities.

For own brand elasticities, marketing-mix actions (mind-set metrics) obtained significant sales effects in 81% (58%) of all cases (taking $p < .05$ as a criterion), as shown in the last two columns of Table 4. For competitive elasticities, marketing-mix actions (mind-set metrics) had significant sales effects in 55% (49%) of all cases ($p < .05$). Thus, a higher proportion of own brand effects relative to competitive effects attained significance, as is common in aggregate response models (Hanssens, Parsons, and Schultz 2001). We focus on interpreting the own brand elasticities because these represent the levers that managers can pull to enhance their brand's performance. Table 4 shows the own effects of marketing-mix actions and consumer mind-set metrics on brand sales, averaged over all estimates. The detailed elasticity estimates appear in Web Appendix A (see Table A4; http://www.marketingpower.com/jmraug10).

Regarding the marketing mix, overall, we find that brand sales are most responsive to distribution, followed by prices, promotions, and then advertising. The cumulative distribution elasticity is 2.424. This is similar to the single estimate (1.868) available from prior literature on frequently purchased consumer goods (Lambin 1976). The "dominance of distribution" results for existing brands complement Ataman, Van Heerde, and Mela's (2008) finding that access to distribution plays the most important role in the success of a new brand. These findings collectively support Hanssens, Parsons, and Schultz's (2001, p. 347) argument that "distribution is one of the most potent marketing contributors to sales and market share" and that "its elasticity can be substantially greater than one."

As for price, promotions, and advertising, the relative magnitude of the estimated elasticities follows those of previous studies. The estimates themselves, which are based on French data, differ somewhat from empirical generalizations, which are mostly based on U.S. data. First, the cumulative sales elasticity for price is –1.734. Given that these are based on four-weekly data, the magnitude of these price elasticities is in line with the work of Tellis (1988) and Bijmolt, Van Heerde, and Pieters (2005), who report own price elasticities of approximately –2.50. Second, promotions, a variable that combines four different promotional instruments, has a cumulative elasticity of .277. This elasticity compares with other studies that separate promotional elasticity from price elasticity: Ailawadi, Lehmann, and Neslin (2001) report a coupon elasticity of .125, and Pauwels (2004) reports a feature elasticity of .111 and a display elasticity of .014. Finally, the cumulative advertising elasticity is .036, with the order of magnitude similar to the advertising elasticities of .05 reported as empirical generalizations in the literature (e.g., Hanssens, Parsons, and Schultz 2001; Tellis 2004; Tellis and Ambler 2007).

Table 4
SALES ELASTICITY TO MARKETING-MIX AND MIND-SET METRICS

	*Average Elasticity**	*Median Elasticity**	*% of Significant Estimates***
Immediate Elasticity			
Marketing Mix			
Price	–.532	–.411	84
Promotion	.146	.137	92
Advertising	.020	.015	72
Distribution	1.311	.978	74
Total			81
Mind-Set			
Advertising awareness	.095	.078	61
Consideration	.103	.028	56
Liking	.222	.174	59
Total			58
Cumulative Elasticity			
Marketing Mix			
Price	–1.734	–.642	76
Promotion	.277	.120	79
Advertising	.036	.037	60
Distribution	2.424	2.740	58
Total			68
Mind-Set			
Advertising awareness	.289	.149	58
Consideration	.374	.093	56
Liking	.590	.519	56
Total			57

*Including significant and insignificant estimates.
**$p < .05$.
Notes: The figures in the table are measured as follows: Marketing mix: immediate and cumulative brand sales volume elasticity in response to a shock to price, promotion, advertising, and distribution. Consumer mind-set: immediate and cumulative brand sales volume elasticity in response to a shock to ad awareness, consideration, and liking.

[9]Although the model allows for dual causality between sales and the explanatory variables, Granger-causality tests show that marketing actions and mind-set metrics more often Granger-cause sales than vice versa. Awareness, consideration, and liking Granger-cause sales for, respectively, 73%, 71%, and 63% of all brands, and sales Granger-causes the mind-set metrics for, respectively, 52%, 60%, and 51% of all brands.

With regard to the issue of how large the effects of consumer mind-set metrics on sales are, the results show that liking has the highest cumulative sales elasticity (.590). Consideration (.374) and advertising awareness (.289) follow.

Effect Timing of Consumer Mind-Set Metrics Versus Marketing-Mix Actions

Although managers need to know that consumer mind-set metrics explain sales, they also need time to act on them, for example, to avoid a drop in liking translating into a sales decline. A relevant measure to examine this issue is the wear-in time, which is the lag before the peak impact on sales is reached (Pauwels 2004). Table 5 shows the wear-in time results.

As for the marketing mix, the mean wear-in time is shortest for promotions (1.02 months), followed by price (1.59 months), consistent with previous marketing literature. Although promotions give consumers incentives to act faster (Blattberg and Neslin 1990), regular price changes do not evoke such a sense of urgency (Van Heerde, Leeflang, and Wittink 2004). Wear-in is even longer for advertising (1.83 months), the marketing action for which the concept of wear-in time was noted first (Little 1979). A new finding is that the wear-in time for distribution is the highest (2.12 months) among the analyzed marketing actions. Plausibly, consumers take some time to notice and then act on increased availability.

Compared with the marketing-mix actions, mind-set metrics typically take longer to reach their peak impact on sales. The wear-in time for advertising awareness is approximately 2.32 months, while those for consideration and liking reach 2.23 and 2.00 months, respectively. Juxtaposed with the result that these mind-set measures have a significant impact on brand sales performance, the findings suggest that collecting and monitoring these mind-set metrics is worthwhile for advance warning purposes. For example, if there is a drop in consideration (with a 2.2-month wear-in time), managers can take remedial action with a change to price or promotions that have a shorter wear-in time (of 1.6 months or less) to prevent any adverse brand performance impact. Likewise, drops in liking may be counteracted by increasing gross rating points and improving the ad copy. Such empirical knowledge may be critical to the development of effective marketing control systems that are capable of improving long-term brand performance (Rust et al. 2004). Overall, the results underscore the strategic importance of consumer mind-set metrics as leading indicators of brand performance.

Table 5

WEAR-IN OF THE LEAD EFFECTS ON SALES

Response to	*Mean Time (in Months)*
Marketing Mix	
Price	1.59
Promotion	1.02
Advertising	1.83
Distribution	2.12
Consumer Mind-Set	
Advertising awareness	2.32
Consideration	2.23
Liking	2.00

Which Marketing Actions Drive Which Mind-Set Metrics?

Although our model allows for dual causality (e.g., between a marketing action and a mind-set metric), we focus on the effect of marketing actions on mind-set metrics because (1) Granger-causality tests revealed that this causality direction was present for a majority of the brands and (2) marketing actions are more directly under management control. To the best of our knowledge, this is the first quantification of the response elasticities of consumer mind-set metrics to marketing-mix actions. As with the results in Table 6, we focus our attention on own effects and include cross-effects with competition as control variables in the VARX model. Table 6 reports both the immediate and the cumulative elasticities averaged over all the estimates. We focus the discussion on the cumulative effects.

Again, we observe the dominance of distribution, which shows the highest cumulative impact on each of the three mind-set metrics. First, the cumulative elasticities with respect to distribution are .887, 1.040, and .517 for advertising awareness, consideration, and liking, respectively. Thus, consumers report more advertising awareness for brands they can observe in the store, which indicates that distribution helps trigger memory links (Alba, Hutchinson, and Lynch 1991). Moreover, they appear to like available brands more and give greater consideration to them. Second, advertising has the highest cumulative impact on advertising awareness (.064), promotions has the highest cumulative impact on consideration (.032), and price has the highest cumulative impact on liking (–.277). Thus, although distri-

Table 6

MIND-SET METRICS AVERAGE (MEDIAN) ELASTICITY TO MARKETING MIX*

Impact on Mind-Set Metric of a Shock to …	*Advertising Awareness*		*Consideration*		*Liking*	
	Immediate	*Cumulative*	*Immediate*	*Cumulative*	*Immediate*	*Cumulative*
Price	.000	–.020	.061	.018	–.049	–.277
	(.001)	(–.001)	(.056)	(.018)	(–.049)	(–.256)
Promotion	.003	.049	.015	.032	–.026	.149
	(.002)	(.052)	(.016)	(.019)	(–.023)	(.138)
Advertising	.027	.064	.005	.020	.001	.002
	(.026)	(.074)	(.004)	(.018)	(.001)	(.003)
Distribution	.483	.887	.490	1.040	.320	.517
	(.465)	(.839)	(.608)	(1.527)	(.400)	(.781)

*Including significant and insignificant estimates.

Notes: The figures in the table are measured as follows: Mind-set response: immediate and cumulative mind-set metric (advertising awareness, consideration, liking) elasticity in response to a shock to price, promotion, advertising, and distribution.

bution dominates other marketing-mix actions in terms of moving the needle on the mind-set metrics, each marketing action can be deployed selectively to improve a specific mind-set metric. Advertising and promotions intuitively increase advertising awareness and consideration, respectively. In contrast, the finding that price negatively affects liking is relatively new (Keller and Lehmann 2006) and may represent the "more for less" attitude of the twenty-first-century consumer (Kotler and Keller 2006).

CONCLUSIONS

Increasing demands for marketing accountability have created a new sense of urgency for marketers to obtain and analyze the right metrics to drive performance growth and demonstrate marketing's value in a consistent manner. The results of this study imply that mind-set metrics should be given new consideration. These metrics have shown their value as diagnostic measures in many companies (e.g., to track brand health), but the results indicate that they also explain future sales performance, beyond the part explained by marketing-mix actions. Across the four product categories and 62 brands examined, the contribution of mind-set metrics is substantial, with almost one-third of the total explained sales variance that can be attributed to these metrics. Therefore, the findings help marketing executives make a case to top management and analysts that building share in customers' hearts and minds indeed translates into improved marketplace performance. The importance of this demonstration is apparent from the current doubts on the empirical and managerial value of incorporating customer mind-set metrics into an integrated market response model.

Classical marketing response models assume that mind-set metrics are redundant information in a model that measures how sales react to marketing actions. According to this assumption, mind-set metrics are just an intermediate step in the model and can be treated as a black box. We demonstrate that mind-set metrics matter, which begs the question of where this additional explanatory power originates. In all likelihood, the contribution of mind-set metrics reflects the effect of variables that are not included in the marketing–sales response models. Perhaps the most prominent of these omitted variables are those that influence the brand experience and the quality of this experience. Product quality, degree of innovation, brand image, and so on, are typically not included in market response models, partly because they are difficult to measure reliably and in a consistent way across different product categories.

Another important result is that mind-set metrics are not just important for retrospective analyses of sales performance. On the basis of the quantification of the wear-in time of the marketing-mix variables and consumer mind-set metrics on sales, we conclude that the analyzed mind-set metrics can be used consistently as early warning signals. Remedial action may then prevent performance decline or turn it around. The estimated wear-in times can also help answer more tactical questions, such as when the plug can be pulled on an apparently ineffective marketing action.

If replicated across different settings, our analyses could provide some key results on the effectiveness of the marketing mix that have important implications for the effective deployment of marketing actions. The importance of distribution for mature brands in fast-moving consumer goods is evident from an elasticity size that by far dominates that of the rest of the mix. Even when available, distribution is often not incorporated into marketing-mix models because of its low variation in the typical three-year weekly marketing data sets for mature brands (e.g., Pauwels 2004). To uncover long-term effects, longer data periods should be examined (our data set covers seven years). Another noteworthy result is that advertising awareness, consideration, and liking are each driven by all four elements of the marketing mix, again with a dominance of the distribution effect. If the impact of distribution changes is the largest, it is also the slowest, with a maximum effect only registered after two months. Advertising in the current study takes seven weeks to reach its peak sales effect, not the several quarters or even years sometimes espoused by ad agencies (Tellis 2004).

For marketing researchers, the findings indicate the value of incorporating perceptual constructs into behavioral outcome models. First, such integrated models have better fit in explaining the "hard" marketplace performance of interest, whether it is measured as sales volume, market share, or revenue. Second, these models provide richer insights and more actionable recommendations to marketing managers. Company performance metrics (including financial criteria), marketing expenses, and consumer mind-set metrics all have their place in the complicated puzzle of marketing effectiveness (Pauwels et al. 2009).

Limitations

This study has several limitations, which qualify the generalizability of the results. First, we investigate only three mind-set metrics: advertising awareness, consideration, and liking. Adding metrics on brand usage and memories to the equation may further increase the explanatory power of the model. Second, because both mind-set metrics and advertising are available for four-weekly periods, we use this largest time interval for all variables. If certain variables (e.g., prices) vary more frequently than others, this could dampen their estimated influence. Third, the data sample covers one country and four fast-moving consumer goods categories. When possible, we compared the results with those of previous research, and the consistency strengthened our confidence that the usefulness of mind-set results in explaining sales is not idiosyncratic to France. However, the reported elasticities may differ across countries. Fourth, we do not know the cost of purchasing mind-set metrics or the profits that could be generated by brand managers using them. Thus, we cannot assess whether the benefits of using mind-set metrics exceed the cost of collecting or purchasing them. Fifth, we aggregate across stores, which could induce bias, though to a lesser extent in the linear models we use (Christen et al. 1997). Likewise, the aggregation across customers should be investigated further: The finding that increases in average liking improve brand sales does not necessarily imply that increases in liking improve brand purchases of each individual consumer (e.g., nonlinear effects may apply at the individual level). Sixth, two sets of people provide the mind-set metrics and the purchase data (which avoids mere measurement bias), which could have introduced some noise in the analyses. Finally, although we focus on brand-level effects, further research could examine the retailer's perspective by using category-level metrics (e.g., category profits) as focal variables.

Further Research

This study is only a first step in answering the call for additional research on linking mind-set metrics to performance in an integrated modeling framework (Gupta and Zeithaml 2006; Marketing Science Institute 2006). A first avenue for further research is to establish empirical generalizations by examining other mind-set metrics, regions, and product categories. Second, although the main finding on the explanatory power of mind-set metrics holds up for different product categories and brands, further research should examine and quantify the extent to which the contribution of mind-set metrics versus marketing mix varies across these categories and brands. Figure 4 illustrates such conditional analysis based on a median split on brand expensiveness. For expensive brands, the contribution of mind-set (marketing-mix) metrics is 17.6% (30.8%), and the corresponding percentage for inexpensive brands is lower, at 14.2% (41.9%). We speculate that expensive brands are likely to have higher levels of consumer involvement than inexpensive brands, which in turn corresponds to a greater role for the consumer's state of mind, as reflected in advertising awareness, consideration, and liking for such brands. Further research on a larger number of categories should explain cross-brand and cross-category variation in terms of, for example, brand age, consumer involvement, product storability, and competitive intensity. The impact of mind-set metrics may also vary for different generic branding strategies (e.g., low-cost players versus innovators) and different phases of the product life cycle. In addition, further research might establish the continuing contribution of marketing actions to both baseline sales and deviations from this baseline.

Third, extensive qualitative data on marketing actions would allow further research to answer *why* mind-set metrics matter in explaining sales. For example, it is possible that advertising increases bottled juice sales only if a certain advertising message (e.g., it is healthful) resonates with an external consumer trend (e.g., toward health-promoting consumption). If the brand broadcasts a mix of such successful and less successful advertising messages over time, its sales effects would be averaged in a typical marketing-mix model relating advertising quantity to sales. However, brand liking only increases with the "high-quality" advertising messages and thus would add to the average advertising effect in our model explaining sales. The same reasoning applies to promotions, for which different executions may differ greatly in their effectiveness (e.g., to include the brand into the consideration set of new customers).

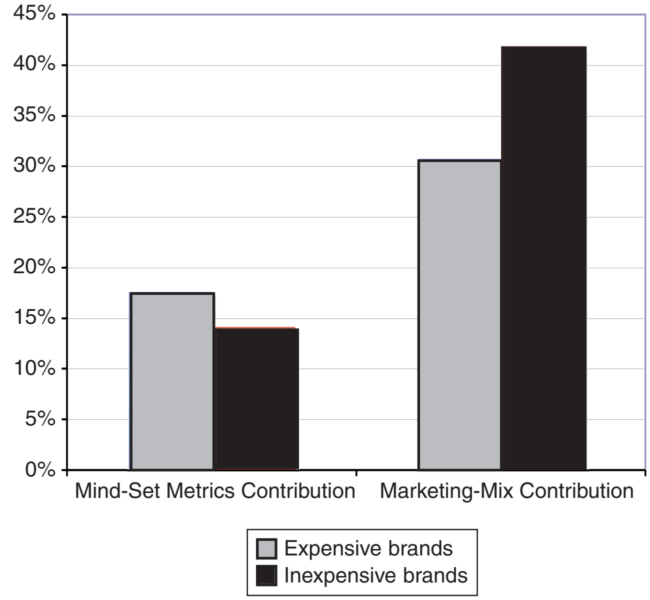
Fourth, the demonstration that mind-set metrics lead sales does not imply that each possible mind-set metric is worth measuring. We needed to make a selection of three metrics, in discussion with the data provider, but mind-set surveys usually collect a large set of metrics. Recent evidence shows that only a few of the sometimes hundreds of available metrics actually lead sales (Pauwels and Joshi 2008). Further research on metric selection is crucial.

A final important topic for further research is the chain of influence of marketing actions, through mind-set effects, to sales performance. Although halo effects may exist among the mind-set metrics (criticized for common method bias), we find that each has a specific effect on sales and is influenced differently by marketing actions. The original hierarchy-of-effects models were criticized for imposing one unidirectional sequence. Instead, dual causality likely exists among mind-set metrics and between mind-set metrics and marketing actions. For example, although consumers may like available brands more (distribution affects liking), retailers are also more likely to stock products that consumers like (liking affects distribution). The current demonstration of the importance of mind-set analysis should renew interest on the sequence of influence and how it differs across categories and brands. Growing this research stream would allow a meta-analysis to provide "best guess" estimates for all links in the metric value chain, so that marketing effectiveness could be tracked within the conceptual framework of Figure 1, even in situations in which specific information on a certain link is missing (Lehmann 2005).

In summary, we urge (1) quantitative modelers to open the black box of customer mind-set metrics, (2) branding experts to consider competition more explicitly when tracking mind-set metrics, and (3) both parties to pay more attention to the role of distribution as a driver of (even mature) brands. We hope that this work contributes to the ongoing efforts of academic research to integrate behavioral with attitudinal data in market response models and helps managers demonstrate the importance of marketing actions in improving company performance.

Figure 4

BRAND EXPENSIVENESS AND VARIANCE EXPLAINED BY MIND-SET METRICS AND MARKETING-MIX ACTIONS



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