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Do Mindset Metrics Explain Brand Sales?

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Is there value in adding customer mindset metrics to sales response modeling? These authors analyze seven years of data for 60+ consumer goods. Their findings suggest that quantitative modelers should include mindset metrics in sales response models, and that branding experts should include competition in tracking research.

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Report Summary
Growing demand for marketing accountability requires marketers to obtain and analyze the right metrics to demonstrate marketing's value in a consistent manner. Until now, researchers have used one of two approaches to evaluating effectiveness: quantitative researchers have modeled the direct sales effects of the marketing mix, while branding experts have tracked customer mindset metrics such as awareness, affect, and purchase consideration.

The authors merge the two approaches, and analyze the added value of including customer mindset metrics in a sales response model that already accounts for the short- and long-term effects of the marketing mix. They ask whether and to what extent mindset metrics really help to explain brand performance. They also try to determine the size and length of the mindset metrics effects on sales and whether mindset metrics are driven by marketing actions. They quantify the size of marketing-mix effects on consumer mindset metrics, and the effects of a brand's and its competitors' metrics on brand sales. They estimate models using a dataset with seven years of four-week measures of sales, marketing actions, and consumer mindset metrics for more than 60 brands of four fast-moving consumer goods.

Their results reveal that awareness, liking, and purchase consideration indeed have an impact on sales, beyond the direct effect of advertising, price, distribution, and promotions. Across the four product categories and 61 brands examined, the contribution of mindset metrics was substantial; almost one-third of the total explained sales variance was attributed to these metrics. Competitors' and a brand's own mindset variables similarly contribute to sales performance.

The authors' methods and findings should help marketing executives make a case for building share in customers' hearts and minds. Their findings suggest that quantitative modelers should include mindset metrics in sales response models, and that branding experts should include competition in their tracking research. ■

Introduction

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.

—Philip Kotler (2003)

The call for marketing accountability has been growing over the past decade, and answering it is seen as key to regaining marketing's standing in the C-suite (Webster, Malter, and Ganesan 2003). As a result, marketers have shown an avid 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 of the research attention has focused on linking marketing actions directly to the company's top-line, bottom-line, and stock market performances (Lehmann 2004; Pauwels et al. 2004; Rust et al. 2004). However, many marketers hold that such output measures have to be complemented by customer mindset metrics. Their main argument is that marketing actions move customers closer to the buying decision in a series of mental steps (Barry and Howard 1990), and that tracking and interpreting the corresponding "mindset metrics" provides early indication of marketing's success (LaPointe 2005). Specific actions that strengthen the competitive position of the brand in customers' "hearts and minds" might not have yet translated into sales. Therefore, mindset metrics (e.g., awareness, attitude, purchase intention) are needed to verify that marketing moved customers in the right direction (Keller and Lehmann 2006).

Both academics and practitioners are divided into two schools in terms of their use of metrics (Anderson and Barry 1979). Quantitative modelers are interested in establishing the short-term and long-term sales and profit effects of the marketing mix (e.g., Hanssens, Parsons, and Schultz 2001). They treat the customer's mind and heart as a black box. In contrast, advertising and branding experts and researchers in consumer behavior focus on the influence of marketing actions on mindset metrics. They typically do not examine the ultimate effect on sales and ignore the impact of competitive actions. There is, however, a call for an integration of metrics in what is referred to as marketing dashboards (LaPointe 2005; Pauwels et al. 2008). The Marketing Science Institute includes the combining of behavioral and attitudinal data to predict brand performance among its research priorities for 2006–2008, and Gupta and Zeithaml (2006) call for research that "incorporates perceptual constructs in behavioral outcome models" (p. 734).

Our main research question is whether, and to what extent, mindset metrics really help to explain brand performance when hard data on sales and marketing-mix expenditures are already available. If both short- and long-term effects of advertising, for instance, are captured in a sales response model, is there any interest in also modeling and therefore measuring mindset effects? If we find that mindset metrics help explain sales in addition to what the marketing mix already captures, then we should also examine to what extent they are leading performance indicators. Our second and third research questions are therefore: (1) how large and long are mindset metric effects on sales compared to marketing-mix effects?, and (2) how are mindset metrics driven by marketing actions?

To answer our research questions, we analyze a dataset with comprehensive information on performance metrics, marketing-mix metrics, and mindset metrics for more than 60 brands in four fast-moving consumer goods categories over a period of seven years. The data were drawn from a consumer household panel, a store panel, and a consumer survey panel. All three are located in France; they are combined in a dashboard-like brand-performance tracker known as “Prométhée.” To address the endogeneity problems, lagged effects, and complex feedback loops that are typical with this type of data (Dekimpe and Hanssens 2007), we used Vector Autoregressive (VARX) models.

Research background

Mindset metrics have a long history in marketing, especially in advertising. Russell Colley’s DAGMAR model (1961) had much influence on the advertising planning process by focusing advertisers’ attention on communication-based objectives and measures, which correspond to our mindset metrics, as opposed to sales-based objectives and measures. Mindset metrics are also the building blocks for many models of how advertising works. The hierarchy-of-effects (HOE) model is one of the best-known examples. The term HOE was coined by Palda (1966) in reference to Lavidge and Steiner’s (1961) model for the predictive measurement of advertising effectiveness. The central idea 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 conation or behavior (purchase, sometimes measured as purchase intentions). The HOE premise is widely accepted in advertising circles in different variations and is integrated in a general model of consumer behavior (Howard and Sheth 1969). More recently, mindset metrics and the HOE idea have also been used in the assessment of brand performance from a customer’s perspective. Keller and Lehmann (2006), for instance, propose five aspects of customer-based brand equity measurement: awareness, associations, attitude, attachment, and action.

The HOE model has been criticized on two points that are both particularly relevant for the broader research on mindset measures. The first criticism relates to the sequence of the stages in the hierarchy. Based on an extensive literature review, Vakratsas and Ambler (1999) suggest that the notion of a temporal sequence is not empirically supported. We identified three formal tests of the HOE sequence and one indirect test. Batra and Vanhonacker (1988) applied Granger causality tests on different sequences among measures of brand awareness, advertising awareness, brand attitudes, and purchase intentions collected in the context of an advertising experiment. Most of the examined links were not statistically significant. Their main conclusions are that attitudes explain purchase intentions only if prior brand awareness and advertising repetition are both high, and that awareness can be driven by, instead of driving, attitudes and purchase intentions. Zinkhan and Fornell (1989) exposed participants in a mall intercept study to ads for fictitious brands and interviewed them one day later to measure ad recall, attitude toward the ad and brand, and purchase intentions. They successfully tested a structural equation model on the traditional HOE sequence. Zufryden (1996) examined the market performance of new film releases as a function of advertising by applying a model based on HOE with advertising expenditures, movie awareness, intention to watch, and the effective purchase of the film ticket as variables. There is no formal test of the model, but the descriptive fit was excellent. Finally, Franses and Vriens (2004) analyzed survey data for five brands of a technology product to see if there was a hierarchy in advertising’s effects on awareness, consideration and brand choice, respectively. They reject the traditional HOE sequence. They also applied a vector error correction model to examine the dynamic effects of advertising and found that, although there are some effects on choice, advertising effects exist mainly for awareness.

Overall, our review shows that evidence on the sequence of effects in HOE is mixed. A likely explanation is that the sequence depends on a number of product category and consumer factors that vary across studies (Batra and

Vanhonacker 1988). We therefore 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 mindset measures.

A second criticism of HOE is even more fundamental for our research: what is the overall value of mindset metrics in explaining sales variation over time? In particular, the current literature lacks a systematic assessment of whether customer mindset metrics matter in the presence of hard marketing and sales data. Indeed, mindset metrics are not popular among quantitative modelers. Gupta and Zeithaml (2006), for instance, observe that "researchers and companies find that they can bypass unobserved metrics" (p. 721).

Palda (1966) was probably the first to express his concerns about mindset metrics in general when he warned against the possible conclusion that "sales as a criterion for effectiveness can be dispensed with and 'substitute' variables used instead" (p. 13). He also wondered if it was really worth the trouble of collecting intermediate measures: "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 . . . ?" (Palda [1966], p. 23). Likewise, Boyd, Ray, and Strong (1972) argued that if communication metrics ultimately are predictive of sales, which they should be, then sales should be measured directly instead. Even today, mindset metrics remain associated mostly with an advertising world that does not want to be held accountable for sales and argues that sales response models capture only short-term effects and miss the long-term sales benefits of brand building. In academia, mindset metrics are typically associated with experimental methods. These methods are very useful for examining which processes are at work, but typically lack external validity in actual market environments and therefore are unlikely to convince marketing-mix modelers of the "sales school" or brand managers who need to justify paying real money for mindset tracking measures.

On the other side, advocates of mindset metrics have hailed them as early warnings of brand performance problems (Ambler 2003; Pauwels and Joshi 2008). The underlying logic is that if the marketing mix becomes less attractive, relative to competitive offerings, the consumer may not react immediately by switching to another brand. Mindset metrics may, however, diagnose a declined interest and offer a chance for remedial action before the bottom line is affected. Another element of this logic is the idea that when consumers decide to switch, it may be difficult to convince them to switch back. It is easier instead to intervene before they actually switch.

At the same time, advances in marketing-mix modeling have demonstrated substantial differences in the long-term versus short-term sales effects of marketing actions (e.g., Dekimpe and Hanssens 1995; Srinivasan, Popkowski, and Bass 2000; Hanssens, Parsons, and Schultz 2001; Pauwels, Hanssons, and Siddarth 2002). In this context, there is an interest in studying mindset metrics because they are slowly moving performance metrics and hence their effects are not immediately visible. Recent research in this tradition has started to focus on exactly when leading indicators that change now will affect sales in the future (Pauwels and Joshi 2008). Such information is important for decision makers who need to not only recognize early warning signals of performance decline, but also take remedial action to prevent it (Pauwels and Hanssens 2007).

Conceptual Framework and Data

Figure 1 summarizes our general framework in visual form. We propose that marketing actions may have both direct effects on sales and indirect effects through consumer mindset metrics. As to the former, the direct effects of

Figure 1
Framework—Marketing Actions, Customer Metrics, and Brand Sales
(Adapted from Lehmann and Reibstein 2006)

price, distribution, and promotion are well documented, and we reported some evidence of the direct effect of advertising on sales in our literature review. In addition, Smith and Swinyard (1983) explain that, when perceived risk and involvement are relatively low, as is the case with the products we analyze, advertising may lead directly to purchase. As to the latter, the HOE model implies that at least some marketing-mix effects first show up in the customer mindset metrics and are then later able to affect sales. We do not formulate hypotheses on the exact nature of these relations, given that our methodology, which we explain below, allows for a complex set of dynamic interactions. Our approach allows for "multiple hierarchies" and for the idea that the impact of a marketing action on the mindset and on sales is neither immediate nor simultaneous, but occurs in "situationally varying and complex patterns of temporal precedence" (Batra and Vanhonacker 1988, p. 24). Our framework also hypothesizes the existence of feedback effects of brand performance on the consumer mindset and on the firms' marketing decisions. Direct, indirect, and feedback effects in combination shape the long-run impact of marketing actions, and the systems (multiple-equation) approach we use adequately captures the various channels of influence that lead to this ultimate effect. In addition, the flexible nature of our econometric specification allows us to uncover new insights on the wear-in and wear-out time.

It is important to put our framework in perspective relative to prior research in marketing. First, advertising campaign testing studies typically consider only the first two boxes in Figure 1, focusing on what marketers do and what customers think and feel (Belch and Belch 2004). Second, brand health tracking studies typically pay attention only to the second box to study what customers think and feel (Keller 2003). Finally, market response models typically address only the first and the third box in Figure 1, focusing on what marketers and customers do (e.g., Hanssens, Parsons, and Schultz 2001). Our framework, in contrast, is comprehensive and includes the complex set of dynamic interactions influencing brand performance.

We use data from Prométhée, a brand performance tracker developed by TNS Worldpanel, which reports the metrics in which we are interested for four-week periods. Prométhée presents a comprehensive, state-of-the-art brand dashboard, with marketing mix, mindset metrics, and performance metrics, by incorporating four data sources. Its key features include a homogeneous definition of which products belong to each brand and a coordination of the regularity of the data collection processes. The details on the four data sources that TNS integrates are as follows:

A nationally representative access panel of households is weekly surveyed on awareness, attitudes, inclusion in the consideration set, and purchase intentions at the brand level of a given product category. For each product category, more than 8,000 surveys are collected per year, but any given household is interviewed maximally twice per year. Prométhée reports four-week averages of the weekly answers for each indicator.

A nationally representative household panel with 12,000 households is used to measure purchases and prices paid. Households use a handheld scanner to scan each UPC and manually enter the price paid by looking at the receipt. Based on the UPC, Worldpanel determines the volume or weight purchased in order to aggregate across different products and package sizes to determine brand sales volume. The price is therefore also a price per volume or weight unit. The use of a household panel for purchases and prices paid assures complete coverage of all retail chains in this market, including hard discounters.

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 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 on promotion for a given observation period. The following forms of promotion are registered: in-store communication, presence in store flyers, price promotions, and bonus buys.

To measure advertising support, two sources are combined. Some media agencies transmit the expenses directly to TNS (e.g., for billboards). For media that are not covered with this method (e.g., TV), all advertisements are identified. Media space prices are publicly available, which then allows TNS to make the conversion from the number of advertisements and their duration to communication expenditures. These expenditures are aggregated across four weeks, based on the date of the advertisement (TV) or the date of the media support availability (press).

For the period between January 1999 and May 2006, we have data on 74 brands from 4 categories, differing on the food versus non-food dimension and in terms of storability: breakfast cereals (21 brands), bottled water (19 brands), fruit juice (19 brands), and shampoo (21 brands). As a brand performance measure, we use sales volume[1] aggregated across all product forms of each brand (in milliliters for shampoo, water, and fruit juice, and grams for cereal). For the marketing mix, our data include average price paid, value-weighted distribution coverage, promotion, and total spending on advertising media.

After discussion with the data provider, we selected from the available consumer mindset metrics the following three measures: advertising awareness, brand liking, and inclusion in the consideration set. This selection aimed at covering the three main stages of the HOE: cognition, affect, and conation. For advertising awareness, survey respondents indicated in a list of all brands present on the market those

Table 1
Descriptive Statistics on Marketing Mix and Mind Metrics
(Average values for four weeks across all brands)

Variables	Cereals	Bottled Water	Fruit Juice	Shampoo
Distribution (value-weighted %)	95.0	91.2	79.6	92.4
Promotions (% of volume on promotion)	15.1	16.8	21.9	24.0
Advertising (in thousands of euros)	251.6	402.1	121.9	359.0
Advertising Awareness (% aware)	16.9	20.6	11.4	18.5
Consideration (% considering buying)	18.4	17.9	18.3	15.9
Liking (scale value)	5.1	5.3	5.6	4.6

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

We also include competitive prices, distribution, promotion, and advertising operationalized as the market-share weighted[2] prices, distribution, promotion, and advertising of the other brands (other than the focal brand) in the category, as recommended by Dekimpe and Hanssens (1999) and Slotegraaf and Pauwels (2008).

Overall, this dataset, with its temporal duration of seven years, the presence of different players with different strategies in different product categories, and wide coverage of the marketing mix as well as consumer mindset metrics, is uniquely suited to address our research questions on the impact of mindset metrics on brand performance. Another important feature, from a measurement perspective, is that all four data sources use an identical definition of the observation periods and the brands. Table 1 provides descriptive statistics on our data.

Estimation 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 have an impact on brand performance over time. For instance, an increase in advertising in a given week may generate a high level of consumer 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 awareness 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 how marketing-mix actions affect the full dynamic system, including mindset metrics and sales performance.

Our empirical analysis proceeds in two steps. First, we estimate the dynamic interactions among sales, ad awareness, brand liking, brand consideration, and the marketing mix (price, promotions, distribution, and advertising) using VARX models, while including competitive variables for the mindset and marketing-mix metrics. Second, we use Generalized Forecast Error Variance Decomposition (GFEVD) and Generalized Impulse Response Functions (GIRF) to quantify the relative influence of consumer mindset measures versus marketing efforts on sales. In doing so, we assess the extent to which the influence of the consumer mindset measures generalizes across categories. Finally, we quantify the extent to

Table 2
Overview of Analysis Steps

Methodology	Econometrics Literature	Marketing Literature	Research Questions
1A. Unit root tests			
Augmented Dickey-Fuller	Enders (2004)	Pauwels, Hanssons, 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. Vector autoregressive model with exogenous variables (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 mindset metrics matter in explaining sales over time. . . ?
Generalized forecast error variance decomposition (GFEVD)	Pesaran and Shin (1998)	Nijs, Srinivasan, and Pauwels (2007)	. . . without imposing a causal ordering on the variables?
B. 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?

which marketing-mix actions drive the mindset metrics. Table 2 provides references that detail each step.

Step 1: Vector-autoregressive model specification

We estimate a 15-equation VARX model per brand, where the endogenous variables are ad awareness, brand liking, brand consideration, average retail price, advertising, distribution, promotion (and corresponding competitive variables), and brand sales.[3] In matrix notation, the model given is by,

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

where A is a 15 × 1 vector of intercepts, Y_t is a 15 × 1 vector of the endogenous variables listed above, and 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. Σ_t is the covariance matrix of the residuals. We use a stepwise procedure to determine the appropriate lag-length p and to eliminate redundant parameters (e.g., Nijs, Srinivasan, and Pauwels 2007). As a benchmark, we also estimate the nine-equation benchmark VARX model obtained by deleting the six mindset metric equations from the full VARX model.

Step 2a: Generalized Forecast Error Variance Decomposition (GFEVD)

VARX estimation is only the first step needed to assess our research questions. Based on the VARX parameters, we derive GFEVD estimates to investigate whether, and to what extent, mindset metrics explain brand sales performance beyond the impact of marketing-mix actions. GFEVD quantifies the dynamic explanatory value on sales of each endogenous variable. Akin to a "dynamic R^2," 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 (Pesaran and Shin 1998; Nijs, Srinivasan, and Pauwels 2007). GFEVD estimates are derived using the following equation:

$$\theta_{ij}^{g}(n) = \frac{\sum_{l=0}^{n} (\psi_{ij}^{g}(l))^2}{\sum_{l=0}^{n}\sum_{j=0}^{m} (\psi_{ij}^{g}(l))^2}, \; i, j = 1, \ldots, \; m.$$

where $\psi_{ij}^{g}(l)$ is the value of a Generalized Impulse Response Function (GIRF) following a one-unit shock to variable i on variable j at time l (Pesaran and Shin 1998).[4] More important, 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." The former (e.g., a past change in 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 mindset 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 based on the GFEVD values at six months, which reduces sensitivity to short-term fluctuations.[5] To evaluate the accuracy of our GFEVD estimates, we obtain standard errors using Monte Carlo simulations (see Benkwitz, Lütkepohl, and Wolters 2001). While GFEVD is the appropriate method to assess our main research question, it does come at a cost: it only allows comparable analyses of brands with stationary sales volumes (83% in our dataset) because the variance for evolving variables is (theoretically) infinite (Pesaran and Shin 1998; Srinivasan, Pauwels, and Nijs 2008).

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

Step 2b: Generalized Impulse Response Functions (GIRF)

Our second and third research questions are examined by inspecting the Generalized Impulse Response functions based on the estimated parameters of the full VARX model. Note from Equation 1 that VARX models capture immediate and lagged, and direct and indirect interactions among the endogenous variables. Based on all these estimated reactions, 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 (Evans and Wells 1983; Dekimpe and Hanssens 1999), 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. Standard errors are subsequently derived using the Monte Carlo simulation approach with 250 runs in each case (see Horváth 2003).

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 may there-

Table 3
Adjusted R^2 for Benchmark Model versus Full Model

	Adjusted R^2 for Benchmark Model		Adjusted R^2 for Full Model	
Category	**Mean**	**Median**	**Mean**	**Median**
Cereals	.360	.339	.441	.404
Bottled water	.503	.574	.617	.642
Fruit juice	.324	.318	.524	.518
Shampoo	.353	.285	.482	.428

fore receive considerable managerial scrutiny; (2) the permanent impact (i.e., the value to which the IRF 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, 2007), to the best of our knowledge this is their first use, to measure the contribution of mindset metrics to brand performance.

Results

First, the unit root tests classify 61 of the 74 performance series as stationary (19 of 21 cereal brands, 17 of 18 bottled water brands, 10 of 17 fruit juice brands, and 15 of 18 shampoo brands). As explained in the methodology section, we focus on these 61 brands (83% of all brands) in our analysis.

Mindset metrics matter in explaining sales

The full model outperforms the restricted benchmark model in explaining brand sales for all the four categories as shown in Table 3. The average adjusted R^2 shows an improvement from .360 to .441 for cereals, from .503 to .617 for bottled water, from .324 to .524 for fruit juice, and from .353 to .482 for shampoos. For both the full model in Equation 1 and the restricted benchmark model without mindset metrics, we report their GFEVD results in Table 4.

In the benchmark model, the marketing-mix actions of price, promotions, advertising, and distribution account for 8.8%, 10.1%, 4.8%, and 2.5% of the variation in brand sales, while competitive prices, promotion, advertising, and distribution account for 3.1%, 4.5%, 3.3%, and 2.0%, respectively. Taken together, a brand's marketing mix and its competitors' marketing mix account for 26.2% and 12.8%, respectively, of the total variation in brand sales. The remaining 61% of the variation in brand sales is attributed to its past sales series, also known as purchase inertia.

Turning to the full model, the brand's own marketing actions account for 22.9%, while competitors' marketing mix accounts for 13.4% of the variation in brand sales. Consumer mindset metrics of awareness (3.5%), consideration (2.7%), and liking (2.3%) together account for 8.5% of the variation, while competitors' mindset metrics of awareness (2.7%), consideration (3.1%), and liking (2.2 %) together account for 8.0% of the variation in past sales. Thus, mindset metrics—a brand's own and competitors'—together account for 16.5% of the variation in brand sales. Past sales account for the remaining 47.2%. Interestingly, the percentage of variation attributed to inertia thus goes down from 61% to 47.2% when mindset metrics are accounted for in the model.

In sum, the answer to our first research question is yes; mindset metrics help to explain sales, even in a model that accounts for long-term effects of a brand's and its competitors' marketing-mix actions. Figure 2 visualizes the

Table 4

Variation Explained by Dynamic Drivers of Brand Sales

(Based on GFEVD analysis; summary across categories)

	Benchmark Model		Full Model	
Response to	**Mean**	**Median**	**Mean**	**Median**
Price	8.8%	5.2%	7.5%	6.3%
Promotion	10.1%	8.6%	7.5%	6.8%
Advertising	4.8%	2.5%	4.4%	2.1%
Distribution	2.5%	1.8%	3.5%	2.7%
→ Marketing-mix contribution	26.2%		22.9%	
Competitive price	3.1%	2.2%	3.6%	2.5%
Competitive promotion	4.5%	2.4%	4.0%	2.9%
Competitive advertising	3.3%	2.5%	3.0%	2.2%
Competitive distribution	2.0%	1.2%	2.7%	1.5%
→ Competitive marketing-mix contribution	12.8%		13.4%	
Awareness			3.5%	2.6%
Consideration			2.7%	1.8%
Liking			2.3%	1.9%
→ Mindset contribution			8.5%	
Competitive awareness			2.7%	1.8%
Competitive consideration			3.1%	2.0%
Competitive liking			2.2%	1.6%
→ Competitive mindset contribution			8.0%	
→ Purchase Inertia	61.0%	63.0%	47.2%	48.8%

contribution of the different dynamic drivers for the benchmark model without mindset metrics versus the full model including mindset metrics. Without mindset metrics, the contributions of the marketing mix and of purchase inertia are overstated by 3% and 14%, respectively.

All four categories studied support this claim, as shown in Table 5. In each category, incorporating the three mindset metrics reduces the purchase inertia part from the majority to the minority in explaining variation in brand sales.

Table 5 also points to the importance of competitive mindset metrics, which contribute almost as much to sales variation as the brand's mindset metrics (8% versus 8.5%). In contrast, competitors' marketing-mix actions contribute only half as much as the brand's own marketing actions, consistent with marketing-mix modeling literature (e.g., Van Heerde, Srinivasan, and Dekimpe 2008). Thus, it appears crucial to measure the "share of minds and hearts" of competitors together with a brand's own share if mindset metrics are used to explain performance.

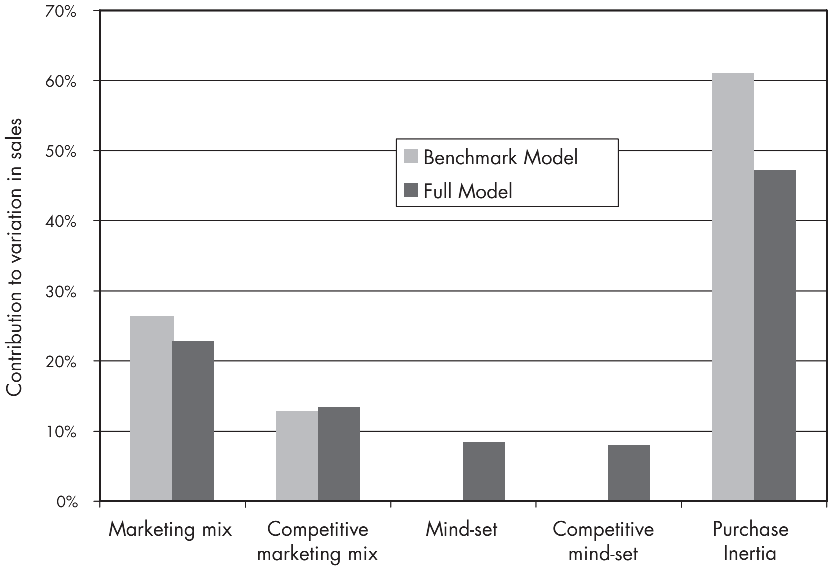
Effect size of consumer mindset metrics versus marketing-mix actions

We examine the response elasticity of sales to the marketing-mix variables and to the mindset metrics. As shown in Table 6, we focus our discussion on the brand's effects of marketing mix and consumer mindset metrics on brand performance.

Figure 2

Dynamic Drivers of Brand Sales

(Summary across categories)



Regarding the marketing mix, we find that brand sales are most responsive to distribution, followed by prices, promotions, and then advertising in each category. The distribution elasticities for immediate and cumulative effects are .978 and 2.740. This range is similar to the single estimate (1.868) available from past literature on frequently purchased consumer goods (Lambin 1976). Our "dominance of distribution" results for existing brands complement Ataman, van Heerde, and Mela's (2006) 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) 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" (p. 347).

As for price, promotions, and advertising, both the size and relative magnitude of the estimated elasticities are consistent with previous literatures (which were mostly based on U.S. data). First, the immediate and the cumulative sales elasticities across categories for price are –.411 and –.642, respectively. Given that these are based on monthly data, the magnitude of these elasticities is in line with Tellis (1988); Bijmolt, van Heerde, and Pieters (2005); and Srinivasan et al. (2004). Likewise, promotions have an immediate elasticity of .137 and cumulative elasticity of .120, very close to the U.S. frozen food category findings in Pauwels (2004). As for advertising, the immediate advertising elasticity is .015, while the cumulative advertising elasticity is .037, in line with the advertising elasticities reported in the literature (e.g., Hanssens, Parsons, and Schultz 2001; Tellis and Ambler 2007).

Turning to the issue of the size of the effects of consumer mindset metrics on sales, our results show that liking has the highest sales elasticity, both immediate (.174) and cumulative (.519). Advertising awareness (respectively, .078 and .149) and consideration (respectively, .028 and .093) follow. This "dominance" of affect over cognition for existing consumer brands has been consistent with consumer behavior insights since the 1980s (Zajonc and Markus 1982) and the recent advertising industry focus on "love for the brand." Interestingly, each of the four categories shows the same elasticity ordering among mindset metrics.

Effect timing of consumer mindset metrics versus marketing-mix actions

While it is important to know that consumer mindset metrics explain sales, managers also need time to act on them, for instance, to avoid a drop in liking that translates into a sales decline. A relevant metric for examining this question is the wear-in time, which is the lag before the peak impact on sales is reached (Pauwels 2004). Table 7 shows the wear-in time results.

As for the marketing mix, the mean wear-in time is shorter for promotions (1.01 months) than for price (1.60 months), consistent with previous marketing literature. While promotions give consumers incentives to act faster

Table 5
Dynamic Drivers of Brand Sales
(Based on GFEVD analysis; summary by category*)

	Breakfast Cereals		Bottled Water		Fruit Juice		Shampoos	
Drivers	**BM**	**FM**	**BM**	**FM**	**BM**	**FM**	**BM**	**FM**
Price	12.7%	10.9%	4.8%	4.6%	9.5%	6.7%	7.9%	7.1%
Promotion	8.9%	6.8%	8.5%	6.6%	9.9%	4.5%	13.4%	11.4%
Advertising	6.2%	5.3%	5.7%	5.6%	1.5%	2.5%	4.3%	3.2%
Distribution	2.0%	2.9%	2.6%	3.3%	2.3%	4.0%	3.3%	4.1%
Marketing mix	29.8%	25.8%	21.7%	20.1%	23.2%	17.7%	28.9%	25.8%
Competitive price	2.1%	2.7%	5.7%	5.9%	1.7%	2.9%	2.1%	2.6%
Competitive promotion	4.9%	4.8%	6.5%	5.2%	2.4%	2.2%	3.0%	3.0%
Competitive advertising	2.9%	2.8%	3.5%	3.3%	3.0%	3.3%	3.5%	2.8%
Competitive distribution	1.3%	2.2%	1.6%	2.5%	3.1%	3.7%	2.8%	2.9%
Competitive marketing mix	11.2%	12.5%	17.2%	16.9%	10.2%	12.1%	11.5%	11.3%
Awareness		3.2%		3.5%		4.8%		3.0%
Consideration		3.7%		1.9%		2.8%		2.2%
Liking		2.7%		1.7%		2.2%		2.4%
Mindset contribution		9.6%		7.1%		9.8%		7.6%
Competitive awareness		3.0%		2.2%		3.5%		2.3%
Competitive consideration		1.5%		4.1%		5.3%		2.4%
Competitive liking		2.2%		2.3%		3.1%		1.6%
Competitive mindset		6.7%		8.5%		11.8%		6.3%
Purchase inertia	59.0%	45.4%	61.1%	47.4%	66.5%	48.7%	59.6%	49.1%

*BM denotes benchmark VARX model and FM denotes full VARX model.

(Blattberg and Neslin 1990), regular price changes do not evoke such a sense of urgency (Van Heerde, Leeflang, and Wittink 2004). Wear-in time is even longer for advertising (1.85 months), the marketing action for which the concept of wear-in time was first noted (Little 1979). A new finding is that the wear-in time for distribution is the highest (2.16 months) among the analyzed marketing actions. Plausibly, consumers take some time to notice and then act on increased availability, as the average purchase cycle of the product categories varies from one to three months. While the other three marketing actions may induce some consumers to accelerate their purchases, distribution is unlikely to do so.

Compared to the marketing-mix actions, mindset metrics typically take longer to reach their peak impact on sales. The wear-in time for advertising awareness is about 2.3 months, while those for consideration and liking reach 2.2 and 2 months, respectively. Juxtaposed with the result that these mindset measures have significant impact on brand sales performance, our findings suggest that collecting and monitoring these mindset 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 awareness and liking may be counteracted by increasing gross rating points and improving the ad copy. Such empirical knowledge may in fact be critical to the development

Table 6

Brand Performance Elasticity to Marketing Mix and Mindset Metrics by Category

(Median estimate)

Brand	Breakfast Cereals	Bottled Water	Fruit Juice	Shampoos	Overall Summary
Immediate elasticity					
Marketing mix					
Price	–.552	–.213	–.754	–.343	–.411
Promotion	.122	.101	.118	.222	.137
Advertising	.021	.015	.006	.022	.015
Distribution	1.327	.974	.982	.935	.978
Mindset					
Advertising awareness	.019	.122	.120	.144	.078
Consideration	.009	.081	.036	.063	.028
Liking	.136	.420	.215	.177	.174
Cumulative elasticity					
Marketing mix					
Price	–.983	–.266	–.290	–1.765	–.642
Promotion	.114	.066	.032	.189	.120
Advertising	.052	.036	.017	.040	.037
Distribution	1.891	3.510	2.709	3.119	2.740
Mindset					
Advertising awareness	.006	.428	.365	.278	.149
Consideration	.000	.118	.172	.098	.093
Liking	.104	.561	1.305	1.203	.519

The figures in the table above are measured as follows:
Marketing-mix response: Immediate and cumulative brand sales volume elasticity in response to a shock to price, promotion, advertising, and distribution.
Consumer mindset response: Immediate and cumulative brand sales volume elasticity in response to a shock to awareness, consideration, and liking.

of effective marketing control systems that are capable of improving long-term brand performance (Morgan and Rego 2006; Pauwels and Joshi 2008; Rust et al. 2004). Overall, our results underscore the strategic importance of consumer mindset metrics as leading indicators of brand performance.

Which marketing actions drive which mindset metrics?

Next, we examine the impact of marketing mix on mindset metrics. To the best of our knowledge, this is the first quantification of the response elasticities of consumer mindset metrics to marketing-mix actions. As with the results in Table 7, we focus our attention on a brand's own effects, while cross-effects are included as control variables in the VARX model. Table 8 reports both the immediate and cumulative elasticities. We focus our discussion on the latter.

The most striking observation is, again, the dominance of distribution, which shows the highest cumulative impact on each of the three mindset metrics. While it is intuitive that consumers are more aware of brands they see in the stores (Alba, Hutchinson, and Lynch 1991),

Table 7
Wear-in of the Lead Effects on Brand Performance

Response to	**Mean Time** (in months)
Marketing mix	
Price	1.60
Promotion	1.01
Advertising	1.85
Distribution	2.16
Consumer mindset	
Awareness	2.30
Consideration	2.21
Liking	2.00

they also like available brands more and give greater consideration to them. After distribution, advertising has the highest cumulative impact on awareness, promotions on consideration, and price on liking. Our results confirm that promotions have negative immediate effects on liking (Keller and Lehmann 2006). In any case, each marketing action may be deployed selectively to improve a specific mindset metric. Advertising and promotions intuitively increase awareness and consideration, respectively. In contrast, our finding that price has a negative impact on liking is relatively new and may represent the "more for less" attitude of the twenty-first century consumer (Kotler and Keller 2006).

Implications for Managers and Researchers

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. From a rich, lengthy, and cross-category dataset, this paper has demonstrated that mindset metrics should be given new consideration. While they have shown their value as diagnostic measures in many companies (e.g., to evaluate ad copy and to analyze what went wrong), they also explain future sales performance, over and above the part explained by marketing-mix actions. Across the four product categories and 61 brands examined, the contribution of mindset metrics is substantial, with almost one-third of the total explained sales variance that can be attributed to these metrics. Our method and findings therefore help marketing executives make a case to top management and analysts that building share in the "customer's mind and heart" indeed translates into improved marketplace performance. The importance of these new insights is apparent from the current doubts on the empirical and managerial value of incorporating customer mindset metrics into models of marketing response.

We also show that mindset metrics are not just interesting for retrospective analyses of sales performance. Through our quantification of the wear-in time of the marketing-mix variables and consumer mindset metrics on sales, we conclude that mindset metrics can be used on an ongoing basis 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 can we pull the plug on an apparently ineffective marketing action?"

Collecting or purchasing mindset metrics evidently has a cost, and for their brand portfolio, brand managers have to evaluate whether the expected benefits exceed this cost. However, we think that with the recent growth of new media and alternative communication campaigns, these benefits have only increased. While direct sales effects of such actions may not be available, it is feasible to measure their effect on the mindset metrics and then plug in the estimated mindset-sales elasticities to complete the metrics hierarchy/causal chain (Lehmann 2005).

Our analyses also provide some unexpected results on the effectiveness of the market-

Table 8

Mindset Metrics Elasticity to Marketing Mix

(Median estimate)

	Awareness		Consideration		Liking	
Impact of . . .	**Immediate**	**Cumulative**	**Immediate**	**Cumulative**	**Immediate**	**Cumulative**
Price	.001	–.001	.056	.018	–.049	–.256
Promotion	.002	.052	.016	.019	–.023	.138
Advertising	.026	.074	.004	.018	.001	.003
Distribution	.465	.839	.608	1.527	.400	.781

The figures in the table above are measured as follows:
Marketing-mix response: Cumulative mindset metric (e.g., awareness, consideration, liking) elasticity in response to a shock to price, promotion, advertising and distribution.

ing mix. A major new finding is the importance of distribution for mature brands in fast-moving consumer goods, as indicated by an elasticity size that by far dominates that of the rest of the mix. Even when available, distribution is typically not incorporated in marketing-mix models due to its low variation in the typical three-year weekly marketing datasets for mature brands (e.g., Pauwels 2004). To uncover long-term effects, it is important to examine longer data periods (our dataset covers seven years). Another interesting result is that 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 registered after only two months. It is also interesting to note that advertising takes seven weeks to reach its peak sales effect in our data, not the several quarters or even years sometimes espoused by ad agencies (Tellis 2004). Moreover, our results suggest that advertising has the largest effect on awareness, distribution on consideration, and price and promotion on liking. These findings have important implications for effective deployment of marketing actions, depending on managerial goals of improving each of the mindset metrics of awareness, consideration, and liking.

For marketing researchers, our findings clearly indicate the value of incorporating perceptual constructs in behavioral outcome models. First, such complete models have better fit in explaining the "hard" marketplace performance of interest. Second, these models allow for richer insights and more actionable recommendations to marketing managers, many of whom are not exactly devotees of the "sales" school espoused by quantitative modelers. Company performance metrics (including financial criteria), marketing expenditures, and consumer mindset metrics all have their place in the complicated puzzle of marketing effectiveness and in increasingly popular dashboard systems (Pauwels et al. 2008).

The current paper is only a first step in answering the call for more research on linking mindset metrics to performance (Marketing Science Institute 2006; Gupta and Zeithaml 2006). Our data sample covers one country and four fast-moving consumer goods categories. An obvious first avenue for future research is to establish empirical generalizations by examining other regions and product categories. We compared, when available, our results with those of previous research, and the consistency strengthened our confidence that the mindset results are not idiosyncratic to France. Moreover, if we find that mindset metrics matter even in long-term marketing-mix models estimated on low-ticket products with short purchase cycles, we can expect they also matter in different settings. Direct replications in these settings and in different countries would nevertheless be welcome.

To answer our research questions, we focused our analysis on the overall average results across the 61 brands in the four brand categories. Future research should examine whether cross-category variation can be explained in terms of, for instance, involvement, storability, and competitive intensity. The impact of mindset metrics may also vary for different generic branding strategies (e.g., low-cost players versus innovators) and different phases of the product life cycle. Moreover, extensive qualitative data on marketing actions would allow future research to answer *why* mindset metrics matter in explaining sales. For instance, it is possible that advertising only increases bottled juice sales if a certain advertising message (e.g., healthy) 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 will be averaged in a typical marketing-mix model relating advertising quantity to sales. However, brand liking will only increase with the "high-quality" advertising messages and will thus 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 in the consideration set of new customers). In principle, modeling "quality-adjusted" marketing-mix actions may thus reduce the importance of mindset metrics in explaining sales. In practice, such marketing quality inferences are very hard to measure accurately, and typically involve the use of mindset metrics, either during an experimental testing phase or ex post (i.e., the specific actions that succeed in increasing mindset metrics and/or sales are retrospectively judged to be of high quality). Future research could thus compare the cost/benefit tradeoffs of obtaining such quality inferences a priori.

Our demonstration that mindset metrics lead sales underscores the importance of mindset metrics, but it certainly does not imply that each possible mindset metric is worth measuring. We had to make a selection of three metrics, in discussion with the data provider, but mindset surveys usually collect several different 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 thus crucial, as data overload is nowadays exacerbated by the fragmentation of media, multichannel management, the proliferation of product lines, and mass customization (Hyde, Landry, and Tipping 2004).

A final important topic for future research is the chain of influence of marketing actions, over mindset effects, to sales performance. Although halo effects may exist among the mindset metrics (criticized for common method bias), we find that they each have a specific effect on sales and are influenced differently by marketing actions. The original hierarchy-of-effects models were criticized for imposing one unidirectional sequence. Our demonstration of the importance of mindset analysis should renew interest in 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 may be tracked within the conceptual framework of Figure 1, even in situations where specific information on a certain link is missing (Lehmann 2005).

In sum, we urge (1) quantitative modelers to open the "black box" of customer mindset metrics, (2) branding experts to consider competition more explicitly when tracking mindset metrics, and (3) both to pay more attention to the role of distribution as a driver of (even mature) brands. We hope our work thus contributes to the ongoing efforts of academic research to combine behavioral with attitudinal data and to help managers demonstrate the importance of marketing actions and metrics in improving company performance.

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Notes

1. 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.

2. 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.

3. VARX model specification requires a test on the stationarity of each endogenous variable. We use the Augmented Dickey Fuller (ADF) test to verify the presence of unit roots in the data, applying the iterative procedure proposed in Enders (2004, pp. 181-3) 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 VAR system is found to be evolving, we implement Johansen's cointegration test to capture a possible long-run equilibrium among the evolving variables (Dekimpe and Hanssens 1999; Srinivasan, Popkowski, and Bass 2000).

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

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

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