What is Important?

Identifying Metrics that Matter

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Abstract
How should one identify and quantify the importance of consumer wants and needs? Using data sets from multiple brand tracking studies, this paper compares various standard market research techniques to Vector Autoregression (VAR) modeling. The analytic philosophy underlying the VAR approach is shown to be consistent and complementary with that of market mix modeling where both the relative and absolute impact on sales of multiple marketing initiatives, including advertising and promotion, are assessed. It is further demonstrated how VAR models and causality testing can identify and quantify those Key Performance Indicators (KPI’s) that relate not only to traditional market research summary metrics such as overall ratings and purchase interest, but also those that can drive brand sales/share and, thereby, be designated as Metrics that Matter (MTM’s).
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Much of the time and many of the resources allocated by companies to custom market research are devoted to answering the deceptively simple, yet highly elusive question of “Why did a customer, non-customer or prospect say or do what they did?” Or, prospectively, “Why did a customer, non-customer or prospect indicate that they were intending some future action?” Typically, the information sought to address these questions is based on methodologies for identifying and quantifying consumer attitudes, beliefs, and opinions as reflective of their underlying needs and wants and relating those insights to reported consumer behavior. The findings are then utilized to assist companies in understanding and, ultimately, in forecasting expected future consumer responses to various marketing initiatives.

From a research perspective, addressing the “why” question is often operationalized through the execution of qualitative and/or quantitative market research studies designed to answer the “what” question; that is, within the relevant competitive set and target universe, “What is or was important to customers, non-customers and prospects at the point in time when the decision was made?” The logic underlying typical market research protocols is that if one can get a valid response to the “what” question then the “why” question can be readily addressed.

Successfully answering the “why” question can enable the accurate and efficient design and channeling of marketing and promotion resources to affect future consumer behavior. Thus, it is not surprising that significant activity for many advertising and market researchers is devoted to developing a knowledge base based on empirical data of consumer wants and needs for their brands and categories of interest. Typically, this task is addressed by researchers drawing upon their own experience, historical research and specific tools such as the Kelly Grid Technique (Kelly, 1963) to postulate the “what’s.” The “what’s” are expressed in the form of attributes, benefits and claims, which can be readily referred to as ABC’s (Lautman, 1993).
Relevant consumer data are collected and analyzed to identify the ABC’s that are important in consumer choice. These ABC’s are then designated as Key Performance Indicators (KPI’s). However, unlike the research approach taken with classical market mix modeling, often the KPI’s emerging from traditional importance assessment techniques tend to be treated as drivers of in-market sales without having undergone the rigorous analytic steps necessary to substantiate that claim.

We will begin with a critical review of the strengths and weaknesses of currently popular research methodologies for assessing “importance.” This exposition will be followed by the description of a relatively new application of a well-known econometric model, Vector Autoregression (VAR). When applied to tracking studies and actual sales data within the framework of a comprehensive brand health model, a VAR analysis will be shown to be a valuable research tool, able to avoid some of the technical challenges inherent in traditional quantitative market research methodologies. Examples from multiple brand health tracking studies will be used to demonstrate the broad application of this research paradigm.

Traditional Quantitative Research Paradigms for Assessing “Importance”

The review presented of classical market research analytic techniques employed for identifying “what is important?” will be limited to verbal quantitative methodologies. Some recent research efforts have focused on developing and implementing quasi-verbal techniques such as picture sorts and metaphor elicitation (Zaltman, 2003), and non-verbal measurement of cognitive and emotional response such as by monitoring brain waves, heart rate and GSR responses or discretely observing consumer behavior such as filming them “at the moment of truth” at the store shelf (either actual or simulated) or in their homes. However, our experience suggests that these techniques, while valuable, currently account for only a small proportion of the research expenditures a typical company invests in understanding consumer preferences and decision making.
Qualitative research techniques, such as in-depth interviews, triads, focus groups and ethnographic research, while often very useful, are traditionally considered pre-quantitative techniques with their findings recognized as not being projectable to general populations without subsequent validation from a representative sample of the relevant universe. Thus, these qualitative efforts tend primarily to be utilized to develop hypotheses for subsequent quantitative research assessments rather than to provide conclusive results.

There are four widely-used quantitative research designs in market research for empirically revealing answers to “why” from “what” questions. Each of these four will be briefly reviewed, identifying their strengths and weaknesses. As shown in Table 1, these four approaches for identifying what is important to consumers can be clustered under two general rubrics, Direct and Indirect (often termed Modeled or Derived) assessment.

### INSERT TABLE 1 ABOUT HERE

**Direct Methodologies**

The most straight-forward methodology for determining what is important to consumers is simply to directly ask the “why” question. This is the protocol typically utilized in qualitative research where consumers are asked to explain and/or provide a rationale for the attitudes, opinions or beliefs that they express or the behaviors that they manifest. A parallel approach exists in many quantitative surveys where consumers are asked in a follow-up to a closed end question to explain “why” they responded as they did. Importance is determined on the basis of “intuitive expert analysis” typically exercised by experienced market researchers who code and aggregate the data.

Conclusions are drawn based on the frequency, sequence, and/or pattern of responses. These efforts produce the well-known “open ended” summary response table. It is generally accepted that the earlier (more “top-of-mind”) and/or the more
frequently a “reason why” is offered, either by a single individual or by a group, the greater is its importance in consumer decision-making. Data can be analyzed at the individual level or aggregate level with the typical scenario being individual responses aggregated up to the segment or population level.

The primary criticism of this intuitively appealing approach is that this methodology, even when responded to anonymously by consumers, suffers from the potential inability or lack of desire of some individuals to communicate openly and accurately what is important to them. This can be a particular concern with self-administered surveys, such as those administered on the Internet, where respondents don’t have the benefit of having interviewers to probe for specifics and clarity. In fact, consumers simply either may not know or be able to introspectively intuit an answer to the question “why.” Not surprisingly, this is more likely to occur when socially sensitive or highly emotional issues are involved.

Another limitation of this method is that the results must rely on the skill of experts not only to faithfully and with great fidelity record consumer responses (if the consumers do not write/type the responses themselves), but also to code and aggregate the data in an efficient and unbiased manner. Thus, careful controls in code development and multi-rater scoring are prescribed to mitigate the risks of inconsistencies and inaccuracies in the summarization process.

Sometimes the aggregation process is bypassed in favor of direct review of the “raw” data by the “users” of the information (often non-market researchers) reading the un-coded verbatim responses. While this approach has the advantage of providing a real-life feel for the voice of the consumer, the primary risk is the potential for less than optimal summarization and conclusions due to information processing limitations and/or lack of experience on the part of the readers. Inaccuracies are often the byproduct of perceptual selectivity and the inherent human decision-making proclivity to interpret information in a manner consistent with historically-driven knowledge, predispositions and biases, sometimes described as mental images, schema, or maps.
The second direct response methodology employs ratings, rankings and/or check-offs where consumers are asked to identify the ABC’s that are more important to them in determining their preferences or choices. Decision tasks can be either constrained or unconstrained in that consumers are either forced (such as with Q sorts and constant sum scales) or not forced (such as with magnitude estimation and Likert scales), respectively, to prioritize ABC’s. While sometimes only one product or service is evaluated, most often this approach is utilized to gain an understanding of what is important to the consumer in choosing and/or developing preferences among a competitive set of alternative products or services in a clearly defined universe.

Unlike with the direct, open-ended response methodology, market researchers utilizing this second direct approach typically believe that they already know the important reasons underlying consumer preferences or choices. Now they want to understand the magnitude of their priority. What is desired is an assessment of the contribution of the various ABC’s, possibly at both an individual and an aggregate level, in determining the reasons for consumer preference or choice (the “why”) as reflected in their ratings, rankings and/or check-offs (the “what”). Not surprisingly, like the first direct method, this approach also can suffer from the potential biases of respondents’ unwillingness or inability to accurately identify what is important to them.

Indirect Methodologies

Two popular indirect measurement and analytic methodologies are designed to reduce the potential social and self-reflective introspective response biases inherent in direct questioning approaches. In both of these methods, consumers are not asked directly to identify what or how much various ABC’s contribute to why an item is preferred. Rather, importance is determined by utilizing statistical analyses applied to survey responses. Since the importance of ABC’s is established across the entire competitive space, not for any single brand, what is determined to be important is assumed to represent the entire category of interest, not any one specific item in the competitive set.
In one common approach, consumers are asked to execute a relatively simple attribution task identifying to what extent a product or service possesses or might possess a particular attribute, deliver an identified benefit or be associated with a specific claim. Typically, the analytic protocol followed consists of a methodology often associated with the PERCEPTOR/ASSESSOR system (Silk and Urban, 1978; Hauser and Urban, 1977; Urban, 1975; Urban and Hauser, 1993). The popularity of this method in common research practice is such that it is extremely rare to find a positioning or market segmentation study that does not employ a PERCEPTOR/ASSESSOR-type derived analysis for importance assessment.

Multiple consumer ratings on relevant ABC’s across a competitive set of brands are aggregated across a sample of consumers and then statistically related to a positively dispositional criterion metric, such as overall favorability, overall preference, overall liking or purchase intent. The importance of each ABC in “driving” behavior is determined based on the strength of its relationship with the overall criterion measure as determined through a simple cross-tabulation (Myers and Chay, undated) or, more commonly, through a statistical analyses designed to quantify systematic variance.

The absence of variance between alternative products or services on an ABC, by definition and design, leads to the conclusion that the ABC is not a “driver” and, therefore, not important in establishing preferences or choices between the alternatives offered. By focusing on variance, the importance of ABC’s is defined in terms of differentiation between the rated items on the ABC’s. Relationships of the ABC’s with the overall criterion can be quantified through various association–based statistical techniques such as correlation and regression.

Technically, an indirect analysis can be executed at the individual respondent or brand level. However, due to a need for sufficient variance and typically a general desire to understand the overall importance of each individual ABC in the competitive space, aggregate level analyses are primarily employed. Quantifying how many people find a specific ABC important is not the focus of indirect assessments, as it can be in a direct analysis.
While clearly possessing some advantages over direct methods, indirect assessment methods still suffer from two important limitations. First, when analyzed using traditional linear regression, the analytic approach is compensatory, meaning that the strengths of brands on some ABC’s would be expected to offset weaknesses on others. Yet, without a potential brand/service successfully achieving if not exceeding a non-compensatory threshold value (“ante”) of a critical ABC, such as having four wheels on a car, providing sufficiently fast service at a quick service restaurant, or killing weeds by a herbicide, especially if the ABC is dominant over all others, a consumer is unlikely to choose that option. This performance hurdle is critical to brand/service selection regardless of how well it performs on other attributes it possesses, benefits it offers or claims it makes and can be termed a Point of Entry (POE) challenge.

A second challenge to this indirect method is that, by definition, only the differentiation between options on ABC’s, that is, uniqueness, has the potential to be “important” since the establishing of preference depends on the existence of variance. Attribute levels achieved and benefits and claims believed and experienced which are valued equally or nearly equally by consumers for all of the alternatives cannot be designated as important since there would be insufficient differentiation between the choice options to generate variance (“restricted range”).

An analysis suggesting little or no importance could occur regardless of whether the options were all rated either as successfully delivering or as severely lacking acceptable performance on an ABC, potentially leads to a managerially illogical conclusion. In fact, in common research practice, it is often found that insufficient differentiation exists between brands or services on intuitively critical attributes, such as “good value for the money,” and many imagery and emotionally-oriented claims for these ABC’s to emerge as “important.” This difficulty highlights what can be termed the Point of Differentiation (POD) challenge.

The second popular derived importance analysis method involves tasks that ask a consumer to make direct choices reflecting their preferences between alternatives (Green and Rao, 1971; Green and Srinivasan, 1990). Unlike with the first derived
method, no assessment of attribution, appropriateness or belief of the attributes, benefits or claims for the choice options is required. Operationally, this fourth method often takes the form of a study design built on a conjoint or discrete choice based task. The research rationale is that by applying a tradeoffs, overall consumer preferences between systematically configured product or service options varying on factors based on ABC’s can be decomposed and appropriately allocated among the underlying ABC's. This partitioning process enables the development of a hierarchy of factor importance (utility) for determining the relative impact of each in driving choices between the options.

Research exercises can be designed to simplify respondent choice tasks by utilizing carefully structured test stimuli based on precise statistical designs (Adelman, 1962) as demonstrated by Wiley, et al. (1984). Sometimes the product/service options are constructed and presented using “full profiles,” with one of several levels of each factor under consideration represented in each choice option. Other times, the options are shown as benefit bundles of factors (typically, pairs, triplets or quadruplets) to make the task more manageable for respondents. Regardless of the format of presentation of the alternatives, the goal is to establish importance priorities for each factor (and levels, if applicable) by utilizing statistical modeling to derive consumer preferences from direct choices made among a set of constrained alternatives.

As with the initially described derived methodology, importance is determined statistically with greater systematic variance defining greater importance. Consumer choices between the constructed alternative product/service offerings are analyzed to identify which of the factors make the greatest contributions in accounting for observed choices. When a factor is composed of levels, importance is still a function of variance--the more “differentiating” the levels, and the larger the range of utilities between the levels, the more “important” is the factor.

Interpretive difficulties are also inherent in this derived importance assessment methodology. First, the design of choice-based studies to identify what is important to
a consumer can be challenging. Often these assessment tools are constrained by the number of options that a consumer can reasonably consider and evaluate at any one point in time.

Second, unless one is dealing with products or services that readily lend themselves to definition into ratio or interval type factors and levels, it is often difficult to create high fidelity exercises for the consumer. Decomposition of products or services into an elementary set of rational and emotional ABC’s elements that are valid, believable and accurate representations of perceived differences between alternatives often is not an easy task. Sometimes to address this challenge, sophisticated scaling exercises are needed to prepare the test stimuli.

Third, design factors, including how choices are presented, the number of levels included, and the number of attributes shown, all have been empirically demonstrated to affect results, thereby challenging the robustness of the methodology. Finally, the reliance on variance as the arbiter of importance in these choice-based system burdens this approach with the same limitations identified with the other derived methodology for determining importance.

Addressing the Limitations

Sometimes, to offset some of the weaknesses of each approach, and, in particular especially those raised by POE and POD issues, data from one of the two direct and one of the two derived approaches are combined into a single analysis. This convergence of methods can demonstrate how the two main types of importance assessment frameworks can augment each other, particularly with respect to those ABC’s identified as unimportant when using one analytic method which have been identified as important in the other.

ABC’s identified as low on direct and high on derived importance are often described as “unrecognized potential motivators;” and, those high on direct and low on derived importance are identified as POE’s. Obviously, application of this dual approach in
practice with the same respondents requires that they take on the increased burden of what may seem to them to be a redundant and time-consuming additional exercise. Alternatively, a carefully matched parallel sample can be utilized to share the response burden.

Not surprisingly, users of each of the four techniques have developed study design and/or analytic enhancements to address their respective limitations. For example, in the direct questioning method, usage of stimuli such as photographs and self-created montages (Zaltman, 2003) have enabled consumers to represent visually what is important to them.

In the indirect methods, various independence assumptions inherent in regression analyses (such as between ABC’s and between brands) are suspended when utilizing standard PERCEPTOR/ASSESSOR-type analyses. A game theory approach termed Shapley Value (Shapley, 1953) has been promoted as a means to address the statistical challenges posed by this relaxation of assumptions and quantify the magnitude of the importance of ABC’s. This boot-strapping analysis procedure normalizes the regression coefficients and relates the contribution of each ABC to the overall R squared (Conklin and Lipovetsky, 2005: Lipovetsky and Conklin, 2001), thereby attempting to mitigate some of the analytic challenges, including negative weights posed by highly correlated (“multi-collinear”) ABC’s. However, since R squares often are low, this method tends to lead to limited differentiation between ABC’s.

The choice method has seen the development of “adaptive” and hybrid models for simplifying and accelerating the choice tasks (Johnson, 1991). These efforts have been incorporated both prior to the initiation of choices by eliminating or simplifying options and during the choice task itself by applying Bayesian analyses to information inherent in early responses to limit the number of subsequent choices needed to obtain stable results. Hybrid approaches, combining both direct and derived importance estimation within a common study design, also have been utilized to reduce what might be perceived to be an onerous number of consumer decisions.
Attempts to incorporate the hierarchical (sequential) nature of some consumer decisions have been made through multi-level models.

Automated analysis of on-line customer reviews have been suggested as a means to help identify relevant attributes and levels (Lee and Bradlow, 2007) and “barter markets” have been employed to improve predictive accuracy, but at what appears to be the expense of increasing the response burden on consumers (Ding, Park and Bradlow, 2007). In terms of improving on the analyses, random effects hierarchical multinomial logit models have extended Luce’s (1959) original approach to allow for individual part-worth estimates as well as aggregated group data (Allenby, Arora and Ginter, 1998; and Ding, Grewal and Liechty, 2005).

The Challenge of Causality

In all four of the techniques cited above consumer responses are analyzed and ABC’s prioritized under the assumption that they can be related to in-market behavior in a well-defined manner reflective of their importance. More specifically by designating an ABC as important, it is implied that significant changes in consumer awareness, attribution and/or belief of that item in a choice option should result in a behavioral or, at least, an attitudinal shift. Marketing priorities can then be set consistent with the discovered pattern of results.

While all four of the traditional analytic methods cited above generally have been accepted as aiding marketers in understanding what is important to the consumer, they all experience a critical challenge, one which was recently popularized in the book “Freakonomics” (Levitt and Dubner, 2005). All of these methodologies identify and quantify what is important to the consumer from data typically collected at a single point in time. Thus, all are subject to the classic statistical limitations inherent in correlation-based analyses and can leave the analyst “fooled by association”; that is, they do not establish cause and effect.
Even if the methodological shortcomings inherent in each of the techniques cited above were rectified, including data reliability established through study replications, none of the four traditional approaches are designed to address this predictive validity challenge. The only way to demonstrate causality is by collecting multiple measurements over time and applying analytic techniques such as lead-lag econometric models to that data. Stated in terms of the conceptual paradigm described here, responses to the “what” question can only answer the “why” question if they are predictive of behavior. Ultimately, companies want to create initiatives that they believe are predictive of future consumer behavior.

Metrics that Matter (MTM)

As a result of having emerged as “important” in multiple traditional assessment methodologies, selected ABC’s, as well as common market research measures of brand presence, such as top-of-mind brand recall and ad awareness, often have been identified as critical to in-market product and service success and therefore termed Key Performance Indicators (KPI’s). Many of these metrics have found their way into senior management reports in the form of Corporate Scorecards and Dashboards.

In the approach to be described here, a distinction will be drawn between KPI’s which potentially may be important to a given brand’s success at a specific point in time and, and those that are important, termed Metrics that Matter (MTM’s). MTM’s are those KPI’s that have been empirically demonstrated to have significant elasticity to drive sales and/or share by contributing to the vitality of a brand over a defined time period within a real world competitive landscape. The identification of MTM’s is a logical consequence of a research progression which can be visualized as a research funnel which begins with many hypothesized ABC’s that may be important to consumer behavior eventually narrowing down and graduating to MTM’s that, by virtue of their elasticity, drive sales/share (see Figure 1).

INSERT FIGURE 1 ABOUT HERE
As shown in Figure 2, traditional market mix modeling analyzes the impact of variations in pressure from specific advertising and promotion marketing initiatives to quantify relative and absolute effects on sales. Similarly, VAR models can be used to analyze variations in consumer response data obtained over multiple consumer survey tracking periods to identify MTM’s. The VAR model addresses the “intervening consumer effect” resulting from marketing and promotion pressure historically not explicitly measured by marketing mix modeling.

**INSERT FIGURE 2 ABOUT HERE**

VAR models can also be viewed as a third stage metric in defining what is important to consumers in that this analysis provides the link between specific consumer attitudes, beliefs and opinions and their impact as reflected in market demand data (see Table 2).

**INSERT TABLE 2 ABOUT HERE**

**Brand Health Assessment: The Brand Health Diamond Model**

Providing a unifying framework for our VAR analysis to identify and represent the causal relationships among MTM’s is a brand health conceptualization which, because of its integrated five facet structure, has been termed the Diamond Model. An earlier version of this model was developed in 1993 for Nabisco to monitor the LifeSavers brand.

**INSERT FIGURE 3 ABOUT HERE**

The Diamond Model provides a parsimonious and management-friendly representation of the dynamic concept of brand health. Unlike some other approaches which are more static (Aaker, 1991; Keller, 1993), this model differentiates in a rigorous fashion between the creators or causes (drivers) and consequences (effects) of brand health. When combined with a time-based data stream, the model is able to represent in a formal manner the dynamic waxing and waning of a brand’s vitality as reflected in
consumer responsiveness to changing market conditions, competitive activity and marketing initiatives.

Each of the five facets is composed of multiple broad-based ABC’s which a detailed review of the market research literature across many categories had identified as “important” in defining “brand health.” Prior client and industry research specific to the area is then used to supplement the ABC list, thereby customizing it for the category under study. All of these ABC’s are characterized as potential KPI’s. The Diamond Model identifies the two facets which are the drivers of brand health, Brand Presence (composed of metrics such as brand and ad/promotion salience) and Brand Impressions (composed of rational and emotional metrics to reflect imagery and product experience); two facets which are consequences of brand health, Brand Attachment (composed of metrics such as loyalty and advocacy) and Brand Value (composed of metrics such as willingness to pay a price premium and purchase without a promotion or incentive); and, one intermediate consequence facet, Brand Consideration, reflecting trial, rejection and patterns of usage.

The arrows in the model represent the hypothesized primary causal directions taken as brand health is created or diminished. For example, (1) low involvement decisions are more likely than high involvement decisions to go directly from Brand Presence to Brand Consideration, (2) high involvement decisions will be more likely to include Brand Impressions, and (3) “mere exposure effects” (Zajonc, 1968) generate some relationships directly from Brand Presence to Brand Attachment, although one would also expect improvement in Brand Impressions. While not presented in the basic model, it is recognized that feedback loops likely will be highly relevant between the model facets and their components. For example, consumer service/product experience as reflected in the KPI’s related to Brand Consideration can be expected to affect Brand Impressions.

The importance of the “paths” between the facets and components of the Diamond Model can be expected to vary with different categories, markets, brands/services, brand life stage, etc. Also, the consumer dynamics inherent in various categories
would be reflected by appropriate ABC’s within the facets. For example, the Brand Value facet for a consumer packaged good (CPG) brand would include outcome metrics such as promotion sensitivity; in the financial space, it would include metrics such as share of wallet for banking and front of wallet for credit cards.

Analytic Approach

The consumer data generation approach used to identify and quantify MTM’s is continuous market/brand health tracking. The objective is to monitor the dynamics of a brand’s “vital signs” on each of the five facets and as contributors to its total health.

By integrating consumer responses in tracking survey data with actual brand sales provided by IRI and Nielsen, we demonstrate how to incorporate Vector Autoregression (VAR) time series modeling (Cromwell, Hannan, Labys, and Terraza, 1994; Enders, 2004: Dekimpe and Hanssens, 2005) into a brand health monitoring program. This analysis will provide an understanding of the importance of each of the ABC’s—that is, the identification and quantification of which ABC’s and, more specifically, KPI’s, have been driving brand sales and therefore can be designated as MTM’s.

Data sets from five consumer tracking programs involving an HBA, three food products, and an OTC analgesic will be used to illustrate the VAR approach. The HBA data set will be of particular interest as we will compare the results from three importance assessment approaches, direct, derived and VAR modeling.

The primary focus of our analysis will be in contrasting the power of VAR results with brand ratings data as typically analyzed in the derived importance PERCEPTROR/ASSESSOR-based system. This MIT-developed system is the one that over the years market researchers have most typically relied upon to identify importance “drivers” in many different types of research studies including A&U’s, segmentation analyses, and brand tracking. Urban (2002), in his autobiographical essay, claimed that over 3000 new CPG products alone have been tested using this
methodology. To provide a full assessment of this technique, three common and frequently used dependent variables were utilized in our derived analyses—purchase intent, overall liking and overall satisfaction—in four separate studies.

While a more detailed of the analytic methodology built around our snack product example is presented in the Appendix, a general overview follows. We conduct a unit root test (Enders, 2004) to assure stationarity of the stochastic process and to avoid the problems of spurious regressions and the violation of the standard assumptions underlying hypothesis testing of the regression parameters. Granger causality tests (Granger, 1969) are used to establish causal relationships in the context of linear prediction as we sought to identify which ABC’s would demonstrate a causal relationship in driving sales and therefore ultimately designated as MTM’s. As each study included many ABC’s, we will only show those that have satisfied these standard tests.

Having established causality, VAR models using OLS estimation are used to quantify the impact on sales for these causal variables. In an unrestricted VAR model, all variables are expressed as functions of lagged values, their own and the values of all others in the system. Based on the estimated VAR parameters, simulations using Impulse Response Functions enabled the evaluation each KPI independently, providing estimates of the effects of MTM’s on sales and share (Sola, undated). As is typical in VAR analyses, seasonal sales spikes were modeled using dummy variables corresponding to the data periods in which such spikes were observed.

We demonstrate both the time trajectory of such effects (lag effects, both short and long term) and their impact on both base and incremental sales, as determined through market mix modeling provided by an independent third party through client managed programs. Base volume is generally assumed to represent long-term effects with incremental volume representing short-term effects attributable to marketing activity.
Results

Two studies in the HBA personal hygiene segment, a segmentation study and an ongoing brand tracking study built on the Diamond Model platform, are analyzed. Both studies are composed of random samples of a target male sample. The segmentation study includes 1000 randomly screened respondents who qualified for the survey based on category use. In the tracking study, two years of data are aggregated into 54 two-week periods, with each period based on approximately 90 category users.

In the segmentation study, consumers were asked directly to rate a battery of ABC’s on how important they were in the selection of a preferred brand. Seven ABC’s, pre-identified by the client as key metrics, were included in both the segmentation and the tracking study. In the brand tracking study, ratings of brands on ABC’s are analyzed using multiple methods. These analyses are VAR models for both base and incremental sales (as determined through market mix modeling), and derived importance analysis with three dependent variables: purchase intent, overall liking and overall satisfaction. To address the issue of all KPI’s not being able to be analyzed in a single VAR model due to the number of data periods available for analysis, KPI’s that passed the causality screen are grouped into facets and stepwise regression analyses conducted.

As shown in Table 3, the VAR results demonstrate that ad/promotion awareness had nearly ten times the impact of any other significant KPI on base sales, clearly qualifying it as an MTM. The VAR models also demonstrate the KPI’s of being able to “allows shaving against the grain” and the satisficing metric of “good enough shave” to be the strongest product/brand MTM sales drivers. Similarly, being portrayed as “ordinary” (not a beauty model), but still “attractive to the opposite sex,” and not “self-absorbed” are the strongest MTM user images and, therefore, not surprisingly, were selected by management to be part of the brand’s future copy platform. Relative to base sales, MTM’s driving incremental unit sales are not as strong, with “worth
paying more for” from the Brand Value facet showing a strong impact. Since every MTM which has a significant impact on incremental sales also demonstrates a significant impact on base sales, movement on those metrics can be expected to improve total unit sales.

Comparing the VAR results with the statistically significant KPI’s seen in the derived importance analysis with purchase intent, overall liking and overall satisfaction as the dependent variables reveals a different pattern of results. None of these three traditional variables shows a significant effect in the VAR analysis. The strongest MTM, ad/promotion awareness, does not emerge as statistically significant in the traditional derived importance analysis with purchase intent or overall satisfaction as the dependent variables, and only has an extremely weak effect with overall liking. Although overall liking and satisfaction generally show higher relationships with the KPI’s, it can be seen that there is very little differentiation between the product/brand features, making setting marketing priorities between them somewhat problematic.

Only the KPI “growing more popular” drops out as weaker than the other product/brand features, and then only with overall liking and overall satisfaction as the dependent variables. Also, “good enough shave” and “allow shaving against the grain,” both of which show a strong impact on base sales in the VAR analysis, do not emerge as significantly stronger than the other product/brand features in the derived importance analysis.

More interesting are the user imagery ratings which show low and/or not statistically significant results in derived importance. The Brand Attachment KPI “brand for people like me” and the Brand Value KPI “worth paying more for” clearly qualify as MTM’s in both the VAR and derived importance analyses. Top box, top two box and mean ratings all demonstrate that high performance on brand ratings or user imagery KPI’s does not necessarily lead to high derived importance or strong performance in the VAR analyses.
While “gives a close shave” is rated significantly higher than any other KPI in the direct importance rating, it is not among the highest scoring in our derived importance analysis and is not observed to be statistically significant in either the base or incremental VAR models, suggesting that it may be a POE. Similarly, the KPI “is technologically advanced,” a claim considered by marketing to be important in the brand’s positioning, and which is found to be an MTM in the VAR analysis, is rated statistically significantly lower in direct importance than any of the six other KPI’s.

Still, there was some agreement between the VAR results and the derived and direct importance ratings. This is particularly noticeable with respect to the relatively high importance scores for the Brand Value KPI “worth paying more for” and the Brand Impression “allows shaving against the grain.” Interestingly, on neither of these claims is the brand rated particularly strongly.

INSERT TABLE 4 ABOUT HERE

Table 4 presents the results of an analysis of two years of survey data for a food product, aggregated into four week intervals of 150 target market respondents. Shown are the results of the VAR analysis, the derived importance analyses for purchase intent, overall liking, and overall satisfaction, and the top box, top two box, and means for the KPI’s.

Unlike in the HBA analysis, a large number of KPIs qualify in the VAR analysis as MTM’s. In fact, every facet of the model incorporates at least one KPI qualifying as an MTM and all five Diamond Model facets are represented by significant unit sales volume. The Brand Attachment facet has the two strongest KPI’s, overall liking and favorite brand, and every brand personality image has a significant impact on sales.

Comparing the VAR results with the derived importance measures demonstrates that many of the KPI’s are recognized to be important in both analyses. Still, it is apparent there are a number of important differences between the two analyses. First, the ad/promotion awareness, the core positioning for the brand and nearly all of the user
images, have derived importance scores much lower than the other metrics, even though the VAR analysis demonstrates that all of these metrics had a large impact on sales. In fact, it can be seen that ad/promotion awareness is among the strongest MTM’s. Also, the brand personality imagery, while strongly associated with the brand, possibly because of its dichotomous ratings demonstrates much lower derived importance scores than the product/brand attributes. However, in the VAR analysis, two brand personality images, “contemporary” and “engaging,” generate more sales than any product/brand feature other than “a kitchen staple.”

Of the three dependent variables in the derived analysis, only overall liking also makes a strong contribution to sales in the VAR analysis. Analyzing the other KPI’s in terms of their correlation with overall liking does not show a pattern of results different from that of the other two dependent variables. This lack of differentiation is not surprising given the relatively high inter-correlation between the three dependent variables.

**INSERT TABLE 5 ABOUT HERE**

Table 5 shows the results of a VAR model for a food (sauce) product. Included in the analysis are 25 periods of survey data in four week intervals of 125 category users.

Two KPI’s, ad/promotion awareness and purchase intent among users, are significant and shown are the base unit sales accounted for by each. The importance of ad/promotion awareness to sales would not have been recognized from the derived importance analysis. Since the market mix model shows that incremental ad/promotion awareness is being driven by television advertising, we conducted a separate VAR share model for television-generated incremental sales. This model shows that user imagery accounted for 86% of the incremental sales driven by television. This can be compared to the product/brand features which, while particularly highly associated with the brand as shown in the ratings, accounts for only 14% of the incremental television-generated sales. Brand movement on the user ratings of “friendliness” and “family pleasing” images has the biggest impact, accounting for nearly two-thirds of the television-driven incremental volume...results
that likely would not have been expected simply by directly comparing their derived importance scores to those of the other user image KPI’s.

Insert Table 6 about here

Table 6 shows the results for a branded snack product and demonstrates the ability of VAR models to address concurrent and lagged effects. Three years of sales data are aggregated into four-week periods of 200 category users. The data shown represents the impact on pound sales for a one-time, one percentage point increase for each MTM.

Interestingly, in terms of Brand Impressions, short term sales are driven by product/brand features. Total sales are driven more by occasions of use— not an unexpected finding in what is generally considered to be an impulse driven category. Product satisfaction, a KPI widely considered to drive snack product consumption, is identified as an MTM, having both short and long term effects. In the derived analysis, overall satisfaction also has the directionally highest correlation with purchase interest and significantly highest with overall liking.

Wear-in refers to the number of periods it takes to reach the respective MTMs peak impact on sales. Wear-out refers to the number of periods the MTM effect lasts beyond the peak period to complete decay. Occasions of use are observed to have a one period (4 week) wear-in period, while product/brand features have an immediate effect. Shown in Figure 4 is the wear-in and decay function for overall product satisfaction; the effect peaked on week 12 and dissipated by week 16.

Insert Figure 4 about here

In terms of relationships of the three dependent variables with the significant KPI’s, overall liking and satisfaction are directionally higher for the Product/Brand Features relative to occasions of use. This may be reflective of the finding that the snack product performed significantly better (all p <.01) on the two product/brand feature KPI’s relative to three out of the four occasions of use KPI’s. In contrast to the derived importance
analysis, the VAR-model shows that the product/brand variables do not have a larger effect than the occasions of use variables on total sales.

Also included in the VAR analysis is an overall measure of brand health, the Brand Vitality Score (BVS)\(^2\). This measure provides a summary metric of the consequences (effects) in the Diamond Model, and is based on purchase intent, overall favorability and overall liking. BVS includes consumers who claim to be familiar with a brand thereby representing less well known brands on a somewhat level playing field relative to better known (often larger) ones. As shown in Table 6, BVS captures both short and long term effects with the impact of movement having a relatively large impact on sales for up to 12 weeks (Figure 5).

**INSERT FIGURE 5 ABOUT HERE**

Given the importance of private label products in this snack category, we also conduct a VAR analysis of the impact of changes in the health of the branded product on private label brands. This analysis shows that significant positive movement on the branded product ratings on “need a lift in the afternoon” and “for on the go” leads to short term sales lifts for private label brands. Furthermore, a one percent enhancement in the overall brand health score, BVS, for the branded product leads to large increases in both short (67,279 pounds) and long term total sales (190,452 pounds) for private label products. Thus, branded marketing/promotion activity which improved the brand equity of the branded product (the category leader) also grew the category.

**INSERT TABLE 7 ABOUT HERE**

Table 7 presents the results of a VAR analysis in the OTC category. Four week aggregations years over approximately two and one-half years yielded over 32 periods of data. Interviews were with approximately 160 target market consumers in the first 13 periods and 320 in each of the remaining periods.
Shown are only the results for KPI’s related to Brand Impressions—specifically, symptom appropriateness, which is generally accepted in the pharmaceutical industry as the key driver of OTC brand selection. Using the results from marketing mix models to parse out the effects of total unit sales and advertising driven incremental sales, the impact on average four week unit sales of a one percent increase on ratings is shown both in terms of its impact on total unit sales (base plus incremental) and on incremental sales solely due to advertising. A clear MTM priority is apparent. Improvement in perceived performance on migraine headaches, muscle aches and backaches is shown to have a greater impact on sales than improvement on general aches and pains, regular headaches, cold/flu and, especially, general strains and sprains.

In terms of sales directly associated with advertising, improvement is less differentiated but is related with higher ratings on appropriateness for “joint pain and stiffness,” “general aches and pains,” and “muscle pain.”

The three derived importance analyses with purchase intent, liking or satisfaction as dependent variables do not show statistically significant differences between the ten symptoms, with all essentially equivalent and each accounting for between 9-13% of the variance. Thus, the derived importance metrics do not provide a clear road map for setting symptom priority for future marketing efforts.

Conclusions

While the acronym for “important” ABC’s, KPI’s and MTM’s, are often used interchangeably in common business parlance (e.g., ConAgra, 2004), as shown here rigorously differentiating between them in relation to determining what is driving market share and sales can provide significant brand health insights and potentially a competitive marketing advantage.

Multiple examples from on-going brand health tracking programs are presented demonstrating how VAR models, when applied to brand health metrics and sales data,
can identify those consumer metrics that have the greatest impact on in-market sales/share. More specifically, the VAR analytic protocol presents an approach for qualifying KPI’s as MTM’s (“brand health levers”) and quantifying the sales impact of each MTM. Also, we illustrated how VAR models can take advantage of the partitioning of sales effects traditionally available through marketing mix modeling to identify which KPI’s are driving different aspects of sales. The ability to appropriately attribute KPI’s to base, incremental, and television advertising driven sales is demonstrated.

The availability of VAR-derived information enables marketers to focus marketing initiatives on those KPI’s expected to have a meaningful sales impact. By allocating marketing and promotion efforts among those MTM’s in a manner reflected of their expected return for enhancement, marketers can implement a formal ROMI (Return on Marketing Investment) analysis to drive resource allocation decisions. For example, assuming that both unaided brand awareness and quality are MTM’s, resource allocations decisions regarding the investment spending needed to leverage additional performance on each of those two metrics could be weighed relative to their expected ROMI.

Since competitive brands can also be modeled, the VAR approach can directly address the challenges posed in identifying POD’s and POE’s by comparing actual ratings or rankings of the brands with the VAR results identifying which ABC’s meet MTM standards for each brand. Line extensions can also be independently evaluated with the goal of identifying MTM’s that can facilitate brand differentiation and portfolio optimization. Private label and store brand products can be modeled, either in aggregate or individually. One of the examples presented clearly demonstrated the unexpected sales lift enjoyed by private label products as they benefited from the marketing initiatives for a market leading, branded snack product.

A VAR analyses clearly demonstrates the value of time series measurement in importance assessment. Assessments of importance at a single point in time cannot take into account lead or lagged effects. Furthermore, consumer metrics that do not
demonstrate a current association with standard static direct and derived assessment techniques would not be judged as important and might even be rejected, even though a dynamic time series analysis might show that they contribute to sales after accounting for significant lead or lag effects. Traditional multiple assessments at different points of time (such as ATU’s executed once or twice a year) or even reliability checks done during the same time period do not adequately address this limitation. In essence, by focusing on trends rather than relying on data from a single point in time, researchers will be less likely to be “fooled by randomness” (Taleb, 2005).

The derived importance techniques that underlie many of the current analyses being used for identifying KPI’s tend to be conducted at the category level. It is presumed that the same KPI’s that drive a category also drive the sales of each of the brands in that category. We believe it is risky to assume that KPI’s that are found to be category drivers are the same for every brand in the category. The availability of an increasing proliferation of alternative product options, multiple need states, and alternative distribution channels, all have led to the definition of many categories becoming “fuzzy,” complicating the creation of competitive sets. Even within well-defined competitive sets, our experience in multiple research projects with VAR models has identified significant differences in “drivers” for different brands.

It is reasonable to assume that the relative importance of MTM’s for a brand will vary as it matures in terms of its own life stage and adoption cycle from being a new to an established product, as competitive brands emerge in its competitive set change, as the market matures and as marketing strategy and activity vary. This would suggest that consideration should be given to updating a VAR analysis on a schedule reflective of a brand’s evolution.

Not all consumer metrics can be expected to demonstrate rapid change as a result of shifts in market and marketing activity. Some metrics, particularly those directly related to a brand experience, are likely to be relatively slow moving signals, dependent on a critical mass of triers/users and purchase cycle patterns. Still, as
demonstrated, in a long-term tracking program even slow moving signals can be monitored and their influence, even if only gradual, detected.

The Brand Presence metrics of advertising and promotion effectiveness (awareness) often are not included in traditional importance assessment methods in their analyses of the drivers of choice and preference. When measures of these effects (including media source, if available) are included in a single brand health survey instrument, VAR analyses can assess their sales impact relative to other metrics underlying the brand health model facets and to the overall vitality of the brand.

The VAR results presented demonstrate the importance of integrating copy testing results with on-going tracking and ultimately MTM development. Consumer recognition and recall of actual advertising, promotions and even a core positioning can be included in the VAR analysis. This enables the setting of message priority to reflect VAR modeling findings in much the same way as media spending strategy tends to be directed by the findings from market mix modeling. Copy testing can confirm if the messages found to be having the greatest sales impact are generating the most consumer registration and greatest playback. Overlaying spending data on the effectiveness of “moving the dial” on these metrics can provide valuable input to a ROMI model.

In general, traditional importance assessment systems have experienced challenges in appropriately measuring what has come to be recognized as the high importance of emotional and imagery related elements in the choice process. One of the advantages of the VAR approach is that there is evidence, as demonstrated here, that brand and user oriented imagery and emotional KPI’s can prove to be MTM’s and have a greater impact on brand sales than product/feature based KPI’s. This is likely due to the longer term nature of the data collection process and larger samples enabling sufficient sensitivity to capture the appropriate variance, even when the absolute levels of attribution of emotional user images relative to product/feature based ABC’s is relatively low.
Future research should compare the predictive validity of the metrics selected by the VAR approach vis-à-vis those selected from other analytical techniques. An analytic methodology commonly used in market research to address the “what” of importance is structural equation modeling (SEM). This approach is based on individual level data and has been proposed to address the causal shortcomings of traditional importance assessment methods. SEM consists of selecting an aggregate dependent variable, such as loyalty, and developing multiple regression models built around a path model. Partial Least Squares (PLS) are often used to quantify associations with the various brand health metrics with greater path coefficients suggesting enhanced importance.

The structure of the Diamond Model of brand health readily lends itself to an SEM analysis following a VAR analysis. SEM can expand on the understanding derived from a VAR analysis by developing a structural model based on prescribed theories of individual-level human decision making behavior. Thus, an SEM analysis can help understand how to drive specific MTM’s which marketing has targeted because of their expected significant impact on sales/share.

While a number of applications of SEM have proven to be interesting and useful to understanding brand health (Morgan, 2000), multiple time periods are rarely, if ever, included in what is typically conducted as a cross-sectional analyses. However, even if multiple time slices were nested in a panel design, this approach would still be restricted by the number of periods in the analysis. Unless time periods are continuous or at least plentiful and consistent from a statistical perspective, this type of cross-sectional analysis presents only a data snapshot, with the statistical analyses capitalizing on one-time chance relationships to give a best fit to the data. Predictions of how well the results will hold up as market dynamics evolve over time are questionable. Other challenges to SEM have also limited its applicability and utilization. These have included: (1) modeling at the category level rather than the brand level when manufacturers are most often interested in understanding which ABC’s will improve the performance of their product, not the category in aggregate, (2) difficulty in interpretation at the managerial level due to often complicated and sometime recursive “paths” between brand health components, and (3) utilization of
criterion measures such as loyalty, which may not relate to sales in a straightforward manner.

It is possible to extend the SEM approach to co-integrate aggregate level VAR time series analyses and thereby test a more complicated theoretical model. Somewhat challenging may be that this combination of data analytic approaches can result in complicated VAR models which will be highly data intensive; and, given the limited amount of consumer data typically available in most tracking programs may not be practical.

The results we present here suggest a need for the development of data fusion models that capitalize on the advantages and minimize the disadvantages of various importance assessment methodologies. Currently, combining traditional direct and indirect methodologies has largely been limited to the identification of POE’s and POD’s. Multi-stage models reflecting hierarchical consumer decision making and competitive set formation would seem to have potential value in this regard. Economists have approached a similar analytic challenge by “stacking” data from different methodologies focusing on the same value assessment to improve statistical efficiency. Interestingly, they have used this approach to combine preferences based on hypothetical scenarios derived from discrete choice and other experiments (which they term “stated” or “direct” behavior) and actual behavior (which they term “revealed” preferences). A two-level nested (conditional) logit model (Hensher and Bradley, 1993) has been suggested to identify and calibrate differences in scale (variance) between data sets while estimating model parameters (Louviere, et al., 2000).

Seeking cause-effect linkages is critical not only for brand health management, but also in nearly every social and political research endeavor. For example, economists have long recognized that when there is an interest among governments to foster economic growth, innovation is an area of great importance. Thus, at the global level, there has been an attempt to relate the consequences of local rules, regulations and political structures to innovative scientific achievements that have attained economic
success. Metrics such as intellectual property, education level and R&D expenditure as reflected by the number of trademarks, patents and overall productivity can all serve, in the language of our model, as ABC’s to be tested for becoming KPI’s and potentially graduating to designation as MTM’s. When sufficient data is available, VAR modeling can serve as a unifying research backbone, providing opportunities to supersede, if not bypass, the typical cross-country business case approach as a method for gaining an understanding of public policy.
Footnotes

1 The authors would like to thank Dr. Vaman Kudpi who executed most of the VAR analyses and Dr. Frank Zinni, Dr. Keith Beauregard, Wayne Robertshaw, and Jane Orner, all of whom provided considerable assistance in compiling the survey data presented.

2 The BVS overall brand health metric was developed by Dr. Orly Maravankin. It has been validated against in market share and sales in multiple consumer product goods (CPG) categories.
Appendix

Our VAR-analysis proceeds in five steps. First, an Augmented Dickey-Fuller test (Enders, 2004) unit root tests verifies the univariate time-series properties (stationarity versus evolution) for each variable. This test addresses the question of whether a variable is mean-reverting (stationarity) or has changed permanently (the null hypothesis) in the data sample (evolution). If sales are mean reverting, no (marketing-induced) change has had a permanent sales effect. Second, we assess whether a metric is a leading indicator of sales performance by testing whether it Granger causes sales. (Granger, 1969; Hanssens, et al. 2001). The assumption underlying Granger causality (or, technically, non-causality) tests is that if an event y is the cause of another event x, then logically event y should precede x. A variable X is said to Granger-cause the performance variable Y if the mean squared forecast error of Y using a bivariate model (i.e., explaining Y using past values for both X and Y) is smaller than that of using a univariate model (i.e., explaining Y using past values of Y only). Granger modeling involves assessing incremental forecasting power and is a statistical test of the joint significance of the other variable(s) in a regression, including dependent variable lags, enabling the testing of the impact on the dependent variable of multiple lag periods.

An important choice is the number of time lags considered in these tests, as choosing a wrong number may lead to the erroneous conclusion that there is no Granger causality (Hanssens, 1980). Because we use these tests to eliminate variables (deleting variables that do not Granger-cause sales at any lag), we apply the tests for lags from 1 up to 6 months and consider a significant test result at any lag to be an indication that the variable is Granger-causing performance.

Third, we estimate the dynamic interactions among sales and all leading performance indicators using Vector Autoregressive (VAR) models. Instead of only treating performance as the dependent variable, VAR models regress a vector of endogenous variables (including performance, customer mindset metrics and marketing actions) on
the past of all endogenous variables, and thus capture complex dynamic interactions among these variables. In matrix notation, the VAR-model is shown below:

$$Y_t = A_t + \sum_{i=1}^{n} \Phi_i Y_{t-i} + \Psi X_t + \Sigma_t, \quad t = 1, 2, \ldots, T$$

where $Y_t$ is the vector of the endogenous variables, $A_t$ is the vector of intercepts and $X_t$ a vector of exogenous control variables, such as trend and seasonal patterns, and $\Sigma_t$ is the covariance matrix of the residuals. The number of lags $p$ is selected by the Schwartz' Bayesian Information criterion, a consistent estimator of lag length (Lutkepohl, 1993).

Fourth, we use the estimated VAR parameters to quantify the dynamic explanatory value of each endogenous variable on performance. Akin to a 'dynamic $R^2$', Generalized Forecast Error Variance Decompositions (GFEVD) provides a measure of the relative impact over time of shocks initiated by each of the individual endogenous variables in a VAR model, without the need to specify a causal ordering among these variables (Pesaran and Shin, 1998; Nijs, et al. 2007). GFEVD estimates are derived using the following equation:

$$\Theta_{ij}^g = \frac{\sigma_{jj}^{-1} \sum_{t=0}^{T} \Sigma_j \sum_{j=0}^{T} A_t \Sigma_i e_{i,j,t}}{\sum_{t=0}^{T} e_{i,t} A_t \Sigma_i A_t e_{i,t}}, \quad i, j = 1, \ldots, m$$

following a one-unit shock to variable $i$ on variable $j$ at time $t$ (Pesaran and Shin, 1998). We allowed the GFEVD sufficient lags (up to a year) to stabilize on the dynamic percentage of performance variation that is explained by a particular variable.

Finally, we quantify the magnitude and timing of the effects of each endogenous variable on performance by means of GIRFs. Based on all estimated reactions in the VAR-model, the impulse response function estimates the net result of a one-unit “shock” to one variable on the performance variable relative to its baseline (its expected value in the absence of the marketing shock). GIRF uses 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. We derive the following three summary statistics from each GIRF: (a) the immediate performance impact on brand sales, (b) the permanent impact (that is, the value to which the IRF converges), and (c) the total or cumulative impact, which combines the immediate effect with all significant effects. In the absence of permanent effects, this cumulative impact becomes the relevant metric to evaluate performance outcomes (Pauwels, et al. 2002). We do not report the statistical significance of this cumulative impact because we accumulate only the impulse response coefficients that are significantly different from zero; the absence of statistical significance is shown as zero cumulative impact. 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).

As an example of our approach, Table A-1 shows the results of the unit root tests, the Granger Causality tests and the Forecast Error Variance Decomposition results for the snack product. For the unit root tests, we display the Augmented Dickey-Fuller test statistic, for which values under -2.88(-2.58) indicate a rejection of the null hypothesis (evolution) at the 95% (90%) significance level. For the Granger causality tests, we report the p-value of the F-statistic for those variables that are Granger causing sales at the 5% significance level. For forecast error variance decomposition, we display the percentage dynamic variation in sales explained by the variable.
Table A-1: Unit Root Test, Granger Causality test and Forecast Error Variance Decomposition for leading snack brand

<table>
<thead>
<tr>
<th></th>
<th>Unit Root Test</th>
<th>Granger Causality (p-value)</th>
<th>% Dynamic Variation in Sales Explained</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sales</td>
<td>-5.92</td>
<td></td>
<td></td>
</tr>
<tr>
<td>I. Brand Presence</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brand Awareness</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Top-of-mind</td>
<td>-6.03</td>
<td>0.038</td>
<td>2.43</td>
</tr>
<tr>
<td>Ad/promotion awareness</td>
<td>-8.16</td>
<td>0.048</td>
<td>1.95</td>
</tr>
<tr>
<td>II. Brand Impressions</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Occasions of Use</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>For on the go</td>
<td>-10.58</td>
<td>0.022</td>
<td>1.72</td>
</tr>
<tr>
<td>Lift in the afternoon</td>
<td>-11.19</td>
<td>0.020</td>
<td>2.31</td>
</tr>
<tr>
<td>Relaxing by yourself</td>
<td>-11.07</td>
<td>0.002</td>
<td>1.35</td>
</tr>
<tr>
<td>Entertaining</td>
<td>-10.98</td>
<td>0.032</td>
<td>1.01</td>
</tr>
<tr>
<td>Product/Brand Features</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Satisfying taste</td>
<td>-11.65</td>
<td>0.004</td>
<td>1.41</td>
</tr>
<tr>
<td>Taste I love</td>
<td>-6.45</td>
<td>0.012</td>
<td>1.02</td>
</tr>
<tr>
<td>III. Brand Consideration</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Regular/Most often</td>
<td>-11.19</td>
<td>0.020</td>
<td>3.62</td>
</tr>
<tr>
<td>Purchase intent</td>
<td>-9.31</td>
<td>0.005</td>
<td>3.55</td>
</tr>
<tr>
<td>IV. Brand attachment</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brand I trust</td>
<td>-11.07</td>
<td>0.002</td>
<td>1.56</td>
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<tr>
<td>Overall liking</td>
<td>-10.14</td>
<td>0.001</td>
<td>4.13</td>
</tr>
<tr>
<td>Favorite brand</td>
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<td>0.043</td>
<td>1.63</td>
</tr>
<tr>
<td>Overall satisfaction</td>
<td>-9.71</td>
<td>0.004</td>
<td>1.35</td>
</tr>
<tr>
<td>V. Brand Value</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Good value for money</td>
<td>-10.18</td>
<td>0.031</td>
<td>1.21</td>
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<tr>
<td>Brand Vitality Score</td>
<td>-11.68</td>
<td>0.009</td>
<td>1.67</td>
</tr>
</tbody>
</table>

Table 6 shows the short-term (same-month) and the long-term (total) sales impact of a 1-point change in the variable (for price: 1 cent change). We also show the wear-in, the number of months it takes until the peak sales impact is reached (0 meaning the peak impact is immediate), and wear-out, number of months with significant effects after peak impact, results. The power of the VAR-model to explain sales (R^2) was 0.89, representing a good model fit. In out-of-sample tests, the metrics produced by the VAR-approach showed a better predictive ability than those obtained by reduced rank regression and by stepwise regression, two other used analytical techniques (Pauwels and Joshi 2008).
Bibliography


Figure 1
The Brand Vitality Sales Funnel

Research and Marketing Input

Metric
Attributes, Benefits, Claims (ABC)
Key Performance Indicators (KPI)
Metrics that Matter (MTM)

Source
Insight/Experience
Association Analysis
Lead/Lag Causal Analysis

Brand Vitality
Sales/Share
Figure 2
Identification of Metrics that Matter
Figure 3
The Diamond Model of Brand Health
Figure 4
Sales Response to a One Percentage Point Increase in Satisfaction
Figure 5
Sales Response to a One Percentage Point Increase
in Brand Vitality Score (BVS)
Table 1
Direct and Indirect Methods for Assessing Importance

<table>
<thead>
<tr>
<th>Assessment Procedure</th>
<th>Data Analysis</th>
<th>Typical Reporting Level</th>
<th>Importance Assessment</th>
</tr>
</thead>
<tbody>
<tr>
<td>Direct Methods</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Open-ended why question</td>
<td>Response frequency, sequence, pattern</td>
<td>Individual/Aggregate</td>
<td>Brand or category</td>
</tr>
<tr>
<td>Importance of specific ABC’s (Attributes, Benefits, Claims)</td>
<td>ABC priority</td>
<td>Individual/Aggregate</td>
<td>Brand or category</td>
</tr>
<tr>
<td>Indirect Methods</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brand attribution on ABC’s</td>
<td>Association of ABC’s with criterion</td>
<td>Aggregate</td>
<td>Category</td>
</tr>
<tr>
<td>Choices between configured (levels of) “product/service” options varying on ABC’s</td>
<td>Utilities based on choices</td>
<td>Individual/Aggregate</td>
<td>Category</td>
</tr>
</tbody>
</table>
Table 2
Stages of Importance Assessment

<table>
<thead>
<tr>
<th></th>
<th>Stage 1</th>
<th>Stage 2</th>
<th>Stage 3</th>
</tr>
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<tbody>
<tr>
<td>Action</td>
<td>Say</td>
<td>Imply</td>
<td>Do</td>
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<tr>
<td>Metric</td>
<td>Direct Importance</td>
<td>Derived Importance</td>
<td>Demand</td>
</tr>
<tr>
<td>Basis</td>
<td>Magnitude and Frequency</td>
<td>Differentiation and Uniqueness</td>
<td>Time-based, lead-lag covariance</td>
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Table 3
HBA Product

<table>
<thead>
<tr>
<th>VAR Unit Sales</th>
<th>Derived Importance</th>
<th>Ratings</th>
<th>Direct Importance</th>
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<tr>
<td></td>
<td>Purchase Interest/</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Liking/ Satisfaction</td>
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</tr>
<tr>
<td></td>
<td>Top Box/</td>
<td>Top Two</td>
<td>Top-Box/ Top Two</td>
</tr>
<tr>
<td></td>
<td>%</td>
<td>Boxes*</td>
<td>Boxes*</td>
</tr>
<tr>
<td>Base</td>
<td>Incremental</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

I. Brand Presence

Brand Awareness

- Top-of-mind awareness: 0.12/0.16/0.17, 5%
- All unaided awareness: 0.05/0.13/0.09, 13%
- Ad/promotion awareness: 2866, NS/0.08/NS, 9%

II. Brand Impressions

Product/Brand Features

- High quality brand: 0.30/0.53/0.54, 47/80, 4.23
- Growing more popular: 0.37/0.28/NS, 23/60, 3.73
- Better shave than others: 101, 71, 0.36/0.61/0.66, 31/64, 3.89
- Good enough shave: 300, 40, 0.32/0.59/0.64, 43/71, 4.08
- Gives a close shave: 0.30/0.57/0.57, 37/75, 4.07, 80/97, 4.75
- Using fewer strokes: 0.30/0.47/0.46, 27/59, 3.79, 48/79, 4.14
- Prevents skin irritation: 0.35/0.52/0.57, 19/53, 3.61, 70/91, 4.57
- Shaving against grain: 299, 0.32/0.50/0.55, 31/60, 3.83, 69/90, 4.54
- Technologically advanced: 116, 0.25/0.50/0.44, 33/70, 3.97, 29/61, 3.77

User Imagery

- Handsome: 42, NS/0.19/0.20, 24
- Attractive to opposite sex: 135, NS/NS/0.18, 19
- Self-absorbed: -97, -0.14/NS/NS, 7
- Ordinary: 271, 109, NS/NS/NS, 17

III. Brand Consideration

- Regularly/occasionally use: 0.37/0.36/0.34, 23, NA
- Purchase intent: NA/0.57/0.55, 9/24, 2.66

IV. Brand Attachment

- Overall liking: 0.57/NA/0.86, 22/41, 4.96
- Brand I trust: 0.32/0.60/0.64, 44/76, 4.15
- Brand for people like me: 201, 120, 0.44/0.59/0.57, 29/58, 3.73
- Overall satisfaction: 0.55/0.86/NA, 33/57, 5.46

V. Brand Value

- Good value for money: 0.37/0.38/0.40, 16/45, 3.37, 65/89, 4.50
- Worth paying more for: 272, 262, 0.40/0.46/0.49, 17/44, 3.30, 41/72, 4.07

*All ratings are five point Likert scales except for overall liking and overall satisfaction which are seven point scales and user imagery, awareness and usage which are dichotomous.
Table 4

Food Product

<table>
<thead>
<tr>
<th></th>
<th>Derived Importance</th>
<th>Ratings</th>
<th></th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Total Unit Sales</td>
<td>Purchase Interest/Liking/Satisfaction</td>
<td>Top Box/Top Two Boxes*</td>
<td>%</td>
</tr>
<tr>
<td>I. Brand Presence</td>
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<td></td>
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<tr>
<td>Brand Awareness</td>
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<tr>
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<td>All unaided awareness</td>
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<td>0.46/0.40/0.34</td>
<td>73</td>
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<td>Ad/promotion awareness</td>
<td>21364</td>
<td>0.22/0.16/0.15</td>
<td>50</td>
<td>NA</td>
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<td>II. Brand Impressions</td>
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<tr>
<td>Core positioning “Authentic”</td>
<td>12823</td>
<td>0.22/0.19/0.13</td>
<td>49</td>
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<td>Product/Brand Features</td>
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<tr>
<td>High quality brand</td>
<td></td>
<td>0.41/0.66/0.60</td>
<td>50/66</td>
<td>5.93</td>
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<tr>
<td>Growing more popular</td>
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<td>0.43/0.62/0.59</td>
<td>32/50</td>
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<td>Has a fresh taste</td>
<td>14317</td>
<td>0.54/0.65/0.71</td>
<td>47/63</td>
<td>5.69</td>
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<tr>
<td>Good for use anytime</td>
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<td>0.55/0.66/0.68</td>
<td>50/66</td>
<td>5.82</td>
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<tr>
<td>High quality ingredients</td>
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<td>0.46/0.71/0.64</td>
<td>47/61</td>
<td>5.79</td>
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<td>Has a taste I love</td>
<td></td>
<td>0.50/0.77/0.72</td>
<td>42/59</td>
<td>5.55</td>
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<tr>
<td>Really different/unique</td>
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<td>0.49/0.54/0.55</td>
<td>32/46</td>
<td>5.15</td>
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<tr>
<td>The best brand</td>
<td>12364</td>
<td>0.62/0.70/0.70</td>
<td>46/60</td>
<td>5.56</td>
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<tr>
<td>A kitchen staple</td>
<td>21333</td>
<td>0.64/0.61/0.60</td>
<td>47/58</td>
<td>5.26</td>
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<td>Brand Personality Imagery</td>
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<tr>
<td>Bold</td>
<td>11174</td>
<td>0.28/0.28/0.27</td>
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<td>NA</td>
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<td>Contemporary</td>
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<td>0.18/0.16/0.15</td>
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<td>Life of the party</td>
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<td>Engaging</td>
<td>16275</td>
<td>0.26/0.25/0.24</td>
<td>34</td>
<td>NA</td>
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<td>Genuine</td>
<td>8821</td>
<td>0.30/0.30/0.29</td>
<td>48</td>
<td>NA</td>
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<td>Vibrant</td>
<td>6911</td>
<td>0.28/0.28/0.28</td>
<td>45</td>
<td>NA</td>
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<td>III. Brand Consideration</td>
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<td></td>
<td></td>
<td></td>
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<tr>
<td>Regular/Most Often Used</td>
<td>19373</td>
<td>0.54/0.49/0.43</td>
<td>60</td>
<td>NA</td>
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<tr>
<td>Purchase intent</td>
<td>NA/0.68/0.65</td>
<td>52/73</td>
<td>4.00</td>
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<tr>
<td>IV. Brand Attachment</td>
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<td></td>
</tr>
<tr>
<td>Overall liking</td>
<td>23315</td>
<td>0.68/NA/0.81</td>
<td>52/69</td>
<td>5.81</td>
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<tr>
<td>Brand I trust</td>
<td></td>
<td>0.48/0.71/0.62</td>
<td>53/70</td>
<td>5.86</td>
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<tr>
<td>Favorite brand</td>
<td>24470</td>
<td>0.52/0.48/0.44</td>
<td>52</td>
<td>NA</td>
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<tr>
<td>Relevant to you/your family</td>
<td></td>
<td>0.57/0.59/0.59</td>
<td>38/50</td>
<td>5.98</td>
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<tr>
<td>Overall satisfaction</td>
<td>0.65/0.81/NA</td>
<td>57/73</td>
<td>5.98</td>
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<tr>
<td>V. Brand Value</td>
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<td></td>
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<tr>
<td>Good value for the money</td>
<td>18780</td>
<td>0.50/0.57/0.56</td>
<td>38/55</td>
<td>5.61</td>
</tr>
</tbody>
</table>

* All ratings are 7 point Likert scales except for purchase intent which is five points and brand personality imagery, awareness and usage which are dichotomous.
# Table 5

**Food Product**

<table>
<thead>
<tr>
<th>VAR Unit Sales</th>
<th>Derived Importance</th>
<th>Ratings</th>
<th>Top Box/Top Two Boxes*</th>
<th>Ratings Mean*</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>TV Incremental %</td>
<td>Purchase Interest/Liking/Satisfaction</td>
<td>%</td>
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<tr>
<td>Base</td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

## I. Brand Presence

- **Ad/promotion awareness**
  - Base: 25,510
  - TV Incremental: 0.18/0.14/0.09
  - Purchase Interest: 55
  - Top Box/Top Two Boxes: NA

## II. Brand Impressions

### Product/Brand Features

- **Meal whole family likes**
  - Base: 7
  - TV Incremental: 0.49/0.58/0.66
  - Purchase Interest: 53/72
  - Top Box/Top Two Boxes: NA

- **Rich taste**
  - Base: 6
  - TV Incremental: 0.42/0.56/0.60
  - Purchase Interest: 46/70
  - Top Box/Top Two Boxes: NA

- **High quality ingredients**
  - Base: 1
  - TV Incremental: 0.39/0.53/0.61
  - Purchase Interest: 45/68
  - Top Box/Top Two Boxes: NA

### User Imagery

- **Friendly**
  - Base: 33
  - TV Incremental: 0.24/0.26/0.26
  - Purchase Interest: 38
  - Top Box/Top Two Boxes: NA

- **Family pleasing**
  - Base: 25
  - TV Incremental: 0.32/0.36/0.39
  - Purchase Interest: 49
  - Top Box/Top Two Boxes: NA

- **Genuine**
  - Base: 18
  - TV Incremental: 0.27/0.29/0.31
  - Purchase Interest: 43
  - Top Box/Top Two Boxes: NA

- **Italian**
  - Base: 10
  - TV Incremental: 0.20/0.23/0.24
  - Purchase Interest: 53
  - Top Box/Top Two Boxes: NA

## III. Brand Consideration

- **Purchase interest (users)**
  - Base: 16,767
  - TV Incremental: NA/0.64/0.64
  - Purchase Interest: 26/56
  - Top Box/Top Two Boxes: NA

## IV. Brand Attachment

- **Brand I trust**
  - Base: 0.48/0.58/0.65
  - Purchase Interest: 58/75
  - Top Box/Top Two Boxes: NA

- **Favorite brand**
  - Base: 0.50/0.51/0.51
  - Purchase Interest: 50/72
  - Top Box/Top Two Boxes: NA

- **Overall liking**
  - Base: 0.66/NA/0.84
  - Purchase Interest: 30/47
  - Top Box/Top Two Boxes: NA

- **Overall satisfaction**
  - Base: 0.64/0.84/NA
  - Purchase Interest: 36/54
  - Top Box/Top Two Boxes: NA

* All ratings are 5 point Likert scales except for overall liking and overall satisfaction which are seven point scales and user imagery and awareness which are dichotomous.
Table 6
Snack Product

<table>
<thead>
<tr>
<th>VAR</th>
<th>Short-Term Sales (lbs.)</th>
<th>Total Sales (lbs.)</th>
<th>Wear in</th>
<th>Wear out</th>
<th>Derived Importance</th>
<th>Purchase Intent/Liking/Satisfaction</th>
<th>Ratings Top Box/Top Two Boxes* %</th>
<th>Ratings Mean*</th>
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</thead>
<tbody>
<tr>
<td>I. Brand Presence</td>
<td></td>
<td></td>
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<td>Top-of-mind</td>
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<td>0.17/0.16/0.13</td>
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<td>Occasions of Use</td>
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<td>For on the go</td>
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<td>88,326</td>
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<td>0.31/0.33/0.30</td>
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<td>Relaxing by yourself</td>
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<td>76,633</td>
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<td>0.37/0.39/0.32</td>
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<td>0.35/0.38/0.39</td>
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<td>Product/Brand Features</td>
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<td>Satisfying taste</td>
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<td>0.36/0.47/0.49</td>
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<td>Regular/most often</td>
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<td>V. Brand Value</td>
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<td>Good value for money</td>
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* All ratings are 5 point Likert scales except for overall liking and overall satisfaction which are seven point scales and awareness, favorite and usage which are dichotomous.
Table 7  
OTC Product

<table>
<thead>
<tr>
<th>Symptom Appropriateness</th>
<th>Effect as a % of total unit sales</th>
<th>Effect as a % of advertising</th>
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</thead>
<tbody>
<tr>
<td>Muscle pain</td>
<td>1.8</td>
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<tr>
<td>Migraine headaches</td>
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<tr>
<td>Backache</td>
<td>1.7</td>
<td>0.0</td>
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<tr>
<td>Sinus headaches</td>
<td>1.4</td>
<td>0.8</td>
</tr>
<tr>
<td>Minor arthritis pain</td>
<td>1.4</td>
<td>0.2</td>
</tr>
<tr>
<td>Joint pain and stiffness</td>
<td>1.0</td>
<td>1.1</td>
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<tr>
<td>General aches and pains</td>
<td>0.8</td>
<td>1.0</td>
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<tr>
<td>Regular headaches</td>
<td>0.5</td>
<td>0.0</td>
</tr>
<tr>
<td>Cold and/or flu</td>
<td>0.5</td>
<td>0.6</td>
</tr>
<tr>
<td>General strains and sprains</td>
<td>-0.3</td>
<td>0.6</td>
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</table>