Beyond “Halo”: The Identification and Implications of Differential Brand Effects across Global Markets

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INTRODUCTION

It is widely accepted among marketing managers and researchers that brands act as a “shorthand device or means of simplification for their [consumers’] product decisions,” (Keller, 2008, p. 6). One way in which brands may play such a role is through a “halo” effect, where the brand name has a consistent impact on a variety of consumer evaluations, even those not directly associated with the brand’s positioning or promise of benefits. “Halo” is a theoretically and empirically robust factor that impacts many different types of consumer evaluations. Indeed, recent research demonstrates the impact of halo effects on factors such as global product quality and corporate social responsibility (Madden, Roth & Dillon, 2012), brand-image associations (Sonnier and Ainslie, 2011), brand extensions (Batra, Lenk & Wedel, 2010), and country of origin effects (Bloemer, Brijs & Kasper, 2009).

Although empirical evidence for a strong and broad impact of brands is compelling, two important questions remain unanswered: First, do brands impact consumer evaluations in ways other than a consistent halo? Is it possible that, while brands may have a strong impact on a variety of consumer evaluations, that impact could vary across the evaluations of different brand benefits? For example, when a consumer evaluates different benefits offered by a Volvo automobile, does the Volvo brand name have a uniform impact on the evaluations of safety, styling *and* performance, or does Volvo impact evaluations of these benefits uniquely?

Second, what is consumers’ *relative* use of overall brand information (which could be captured in a halo effect) vs. detailed attribute-specific information? Research demonstrates that “brand” is not the only type of information considered by consumers, so “halo” is not the only factor impacting consumer evaluations. When consumers evaluate branded offerings, they construct their evaluations from a combination of two mental sources: one containing overall brand information and another containing detailed attribute-specific information (Dillon, et al., 2001). Consider these two sources "informational buckets." Consumers develop their evaluations by drawing some from each bucket, so that part of an evaluation is pulled from what they know about a branded offering's attributes, features, ingredients, etc., and part of it comes from what they know about the overall brand based on its positioning in the marketplace, established through the brand's promise of benefits, advertising, word-of-mouth, etc. When Keller (2008) describes brands as "shorthand," he is referring to the overall brand bucket and suggesting that consumers draw deeply from it, that it plays a significant role in helping consumers make choices. But this does not mean that the details don't matter. Rather, consumers use both buckets to develop their evaluations, but to different degrees (Dillon, et al., 2001).

Using the analogy of mental "buckets," our two questions can be restated as follows: First, does a consumer take a single draw from the brand bucket to evaluate every benefit (i.e., equal brand effect across benefits), or do consumers take a new (and potentially different) draw from the brand bucket each time they are asked to evaluate specific benefits (e.g., differential brand effects across benefits)? Second, to what degree do consumers rely on the brand bucket vs. attribute bucket to evaluate a specific benefit?

We test these two managerially important questions by first extending an established model for decomposing evaluations of branded offerings into overall brand and detailed attribute-specific sources (Dillon, et al., 2001) to investigate whether consumers indeed draw differently from the brand bucket across benefits, what we call "differential brand effects." While brand halo certainly may exist for certain brands at certain times (e.g., as may have been the case recently for Apple), we find in real market data that in many instances brand effects vary across benefits. Thus our methodology can help managers identify the specific benefits on which the overall brand (vs. detailed attribute-specific information) has the greatest impact, allowing them to adjust branding or positioning strategies or advertising copy.

In addition, we extend the basic model to allow for correlations among brands and thereby identify any brand relationships that may exist among offerings in the marketplace. While the basic model assumes branded offerings to be independent, the presence of multiple offerings under a family brand in the same market would suggest that relationships should exist among offerings within the brand family.

The primary contributions of this paper are twofold. First, we provide evidence for a differential impact of "brand" across benefits. This differential impact may be assumed by managers and "easily accommodated" by extensions of existing models, but has never explicitly been demonstrated with live market data. Second, we demonstrate the ability to track the relative use of the brand vs. attribute buckets, which helps brand managers balance their communications emphasis on detailed attribute-specific information or overall brand information as the situation may dictate. While managers may *expect* that consumers do draw different amounts from the different buckets for different benefits, it is quite different to have a simple methodology that allows managers to *see* and react to such changes. In the following sections, we first discuss the conceptual foundations of our model and how we accommodate differential brand effects. We provide the sequence of steps that other researchers can employ to do similar analyses. The model is then applied to 9 product markets containing 55 branded offerings from around the world, illustrating the varying degrees of differential effects of brand across a variety of benefits. We demonstrate that the model is able to capture the relative use of the brand vs. attribute buckets, and finally show that an extended version of the model is able to capture known and expected relationships in the market among members of a brand "family."

LITERATURE REVIEW

Mental Sources of Brand Ratings: Support for Differential Effects

Consumer evaluations of branded offerings are impacted by a variety of factors such as brand familiarity, accessibility of information influenced by usage, need to justify a prior decision, halo effects, country-of-origin effects, order effects, and so on, that potentially create artificially high correlations among survey items for a single brand. While there is great concern about such effects and their impacts on consumer ratings, most models assume that these effects *equally* impact the evaluations of all benefits for a particular branded offering (e.g., Batra, Lenk & Wedel, 2010; Bloemer, Brijs, & Kasper, 2009; Dillon, et al., 2001; Gilbride, Yang & Allenby, 2005; Madden, Roth & Dillon, 2012; Sonnier & Ainslie, 2011). For example, Gilbride, Yang & Allenby (2005) propose models to account for simultaneity within consumer data caused by order effects of brands on a questionnaire, accessibility of brand information based on prior usage, halo effects, and justification bias, and in each case they define a parameter that is specified at the household (h) and brand (i) level, but not the benefit (j) level. [1] This approach assumes that all brand effects have a consistent impact on and across all benefits for a specific offering, i.e., a halo effect. Although halo effects, by definition, should produce a consistent impact across all brand-benefit ratings, we suggest that brand may play a differential role, depending on the particular brand-benefit in question. Below we offer our rationale for such a belief.

Brand-Benefit Beliefs

A “brand-benefit belief” is defined as the consumer’s belief about the degree to which (or whether) a branded offering provides a specific benefit. Although “branded-offering-benefit belief” is more accurate, we use the shorter term because when branded offerings are presented to consumers on surveys, they are presented within the context of a specific category. For example, in this paper, we explore the paper towel, toilet tissue, oral care, and skin care categories. Assume a brand called “Fortune” produced offerings in all four categories. The brand-benefit beliefs evaluated on the type of consumer survey from which our data come would apply specifically to those offerings in the focal category (e.g., oral care offerings). Thus, brand-benefit refers to a particular benefit as it applies to Fortune’s oral care product (i.e., Fortune’s oral care offering’s ability to whiten). The same would be true even if Fortune had multiple offerings in the oral care category (e.g., Fortune Sensitive, Fortune Whitening, Fortune Fresh, etc.). In such cases, the complete offering (brand) name would be provided to consumers who would be asked for their brand-benefit beliefs regarding how well each of Fortune’s branded offerings performed on benefits such as whitening, tarter protection, fresh breath, etc. Thus, when we subsequently refer to “brands,” we mean specific branded offerings; that is, brands as they would be encountered by consumers on a survey.

The collection of all the brand-benefit beliefs for a brand (note: branded offering) is termed “brand beliefs.” When evaluating brand-benefits, consumers draw upon overall or general information about the brand along with information about specific product attributes that may contribute to, or provide, the benefit (Hutchinson & Alba, 1991, 2008). These two sources of information (brand, attribute) may be combined to evaluate individual benefits. Dillon, et al. (2001) already have demonstrated the existence of the two sources of information; therefore, we offer only a brief theoretical justification for this view of brand-benefit evaluations below, as it may help the reader understand the dual impact of "brand" and "attribute" information across a variety of brand-benefits in the model we propose.

Cognitive Processes Underlying Brand-benefit Beliefs

When consumers are asked to evaluate brand-benefits, their responses are based both on the information they have previously stored in memory and how it is activated (Lynch & Srull, 1982). Activation or retrieval of this information can be through either overall associations with the brand and/or more detailed associations with the product and/or its category (Boush & Loken, 1991; Keller, 1993). Three streams of literature provide insight into how consumers use these two sources of information and suggest the possibility of differential effects.

First, the spreading activation model (Anderson, 1983) posits that information stored in memory is retrieved through a variety of paths. Paths will have a high probability of activation if the link between two nodes is strong (e.g., the path between the brand Crest and the benefit of cavity prevention). Other paths will have a low probability of activation due to either weak associations or interference from stronger associations for other brands, making such information unavailable (Jewell, Unnava, Mick & Brucks, 2003; Kent & Allen, 1994; Kent & Kellaris, 2001; Unnava & Sirdeshmukh, 1994). For example, the strong overall brand association in memory between Crest and cavity prevention may interfere with the direct path between Gleem and cavity prevention, forcing a respondent to use an indirect path: The respondent may have to think about whether Gleem has an ingredient such as fluoride that would provide the benefit of cavity prevention. Ultimately, respondents may believe that both brands provide the benefit, but in the case of Crest, the belief would come from the strong overall association of the Crest brand with the benefit of cavity prevention (direct path); whereas, in the case of Gleem, the belief would come from *constructing* an evaluation by considering detailed attribute-specific information related to Gleem's ingredients (indirect path). Likewise, the Gleem brand may have a strong direct association with whitening, while the Crest brand may have a much weaker association with the benefit. This example not only highlights the existence of multiple sources of information, but also suggests that the impact of brand may vary across benefits.

Second, the categorization literature suggests that if an object being evaluated can be categorized immediately and with little effort, then category affect (i.e., the brand effect) is transferred immediately to the object (Loken, 2006). If categorization is difficult, then individuals must utilize a piecemeal processing to evaluate the object (i.e., specific product attributes). For example, based on its overall reputation established over time and reinforced in advertising and earned media, consumers may believe that Volvo is a "safe brand," even if they never owned or had any specific personal experience with the brand. Further, Volvo may be the "standard of comparison" (Loken & Ward, 1987; Mervis & Rosch, 1981) with respect to the category of "automobile safety," making Volvo the "most typical" example of a brand that has this benefit. This would cause the evaluation of other brands to be made by thinking in detail about their specific attributes (e.g., number of airbags, size and weight of the automobile) that may give rise to the safety benefit (Boush & Loken, 1991). That is, to evaluate other brands on "safety," an evaluation must be *constructed* from those details stored in memory that are linked with the other brand and related to the safety benefit; no overall shortcut exists (e.g., Brooks, 1978; Cohen, 1982; Fiske, 1982; Boush & Loken, 1991). This does not mean that other brands cannot be rated as safe – but it does mean that if Volvo and another brand are both rated as safe, then consumers may have developed those beliefs from different mental sources of information: strongly associated overall brand information based on Volvo's reputation and positioning, versus a constructed evaluation based on detailed attribute- or feature-specific information for the other brand(s). Obviously, the use of category or brand versus piecemeal information would depend upon the benefits in question. For certain benefits, the brand would be useful and have a large impact (e.g., Volvo and safety), while for others it could be less impactful or even negative (e.g., Volvo and styling). When consumers consider whether a brand provides certain benefits, they in essence conduct multiple categorizations, one for each benefit, in which case we could expect varying reliance on overall brand vs. detailed attribute-specific information.

Third, the brand extension literature clearly assumes the *existence* of the two sources and also identifies the *use* of these two sources in brand-related decisions. Meyvis & Janiszewski (2004) focus on the accessibility of product attributes versus more generalized brand associations. “Weighing the importance” of the two sources and focusing on the “accessibility” of the two sources requires their existence and also allows for differential importance and accessibility. Additionally, research has found the need for identifying “fit” with a parent brand in an extension strategy (Barone, et al., 2000; Bottomley & Holden, 2001; Klink & Smith, 2001; Loken, 2006). If the fit is not easily determined at the brand level, then evaluations are made in more of a piecemeal, attribute-based fashion. Fit clearly can differ across benefits.

In summary, consumers may be more likely to use overall brand information to evaluate brand-benefits when there is a strong link in memory from the brand to the benefit, when the benefit is seen as typical in the category and the brand in question is also considered typical, or when a benefit has a high degree of “fit” with a brand’s image, reputation or positioning. In other cases, an evaluation must be *constructed* from detailed attribute-specific information, which is embedded in a vast network of brand and category knowledge. More importantly, these frameworks suggest varying degrees of impact of overall brand information on evaluations through different strengths of association, interference, category ties, beliefs, or fit.

Researchers have demonstrated the use of the two mental sources of information for making brand-related evaluations, and their work clearly supports the possibility of differential brand effects. What remains to be seen is whether the brand has a differential impact across brand-benefits in actual market data. In the next section, we address how we can analyze consumers' stated brand beliefs to uncover not only the sources used to develop those beliefs (i.e., brand vs. attribute buckets), but also whether the relative use of the two mental buckets differs across brand-benefits.

OPERATIONALIZING THE SOURCES OF BRAND-BENEFIT RATINGS

Using a procedure similar to that first proposed by Dillon, et al. (2001), and subsequently adopted widely in the marketing literature (e.g., Batra, Lenk & Wedel, 2010; Madden, Roth & Dillon, 2012; Sonnier & Ainslie, 2011), we empirically address a brand's impact across brand-benefit beliefs by decomposing brand-benefit beliefs into overall brand sources and detailed attribute-specific sources. We first describe our model, which identifies the brand versus attribute effects in consumer brand-benefit evaluations, but unlike previous models allows for differential brand effects. The model is then applied to a set of data representing multiple brands from nine global product markets.

Conceptual Framework

Drawing from the previous discussion, our conceptual framework assumes that consumer brand beliefs come from two mental sources: one related to overall brand information (the *brand source*) and the other to detailed attribute-specific information (the *attribute source*). Figure 1 provides an overview of the conceptual model based on three benefits for two brands. The rectangles represent consumers' brand-benefit beliefs – the manifest variables or observed data that come from the survey. For example, in the laundry detergent category, consumers may be asked for their beliefs about whether (or to what extent) a brand provides the benefits of whitening or softening. These beliefs can be measured in multiple ways, ranging from metric ratings to the "checks" that consumers provide in a "pick any" task. This survey data is the input to our model.

The top ovals represent the latent brand source for each set of brand beliefs. These brand sources are the highest-level (i.e., top-of-mind) and/or most easily accessible overall brand associations in memory (Punj & Hillyer, 2004). The brand source may be composed of either a "rolled-up" or summary evaluation (e.g., Sujan, 1985) or an overall association built over time through effective positioning (e.g., FedEx and "overnight delivery" or Volvo and "safety").

[Insert Figure 1 Here]

The bottom ovals represent the latent attribute source for brand-benefit beliefs, generally, the mental network of detailed product and category knowledge that applies to the benefit in question. This attribute source contains the ingredients, recipes, formulations, attributes or features *that give rise to* particular benefits, such as the ingredient bleach providing the benefit of whitening, or whole grains, antioxidants, prebiotics and organic ingredients, in combination, providing the benefit of "healthy." Note that the brand-benefit that consumers are asked to evaluate (e.g., whitening) is distinct from the attribute(s) or ingredient(s) which may *give rise to* the benefit (e.g., bleach), and multiple attributes or ingredients may work together to deliver a brand-benefit (e.g., in the case of "healthy").

Continuing with the laundry detergent example, we are interested in how much of a consumer's evaluation of a brand on, say, softening (a performance benefit) comes from overall brand information (e.g., because the brand is strongly positioned on the softening benefit), vs. how much of that evaluation comes from a thoughtful consideration of the ingredients or other attributes of the brand that give rise to the softening benefit (e.g., the inclusion of Downy as an ingredient, as in Tide with Downy). Further, within a brand, we are interested in whether the brand has a consistent impact on evaluations of both whitening and softening (that is, do consumers rely equally on overall brand information to evaluate both whitening and softening), or whether the brand is more impactful on one vs. the other (i.e., a differential effect).

Capturing Brand and Attribute Effects

The goal is to decompose brand-benefit beliefs into two sources – brand versus attribute. The degree to which consumers rely on the brand source versus the attribute source to provide their brand-benefit beliefs is represented by the loadings from the brand source (β) or attribute source (α) to the benefits (i.e., brand→benefit or attribute→benefit loadings; note that in this notation, "benefit" is actually brand-benefit). Higher reliance on overall brand information to evaluate brand-benefits should result in larger brand→benefit loadings than in situations where consumers devote more cognitive resources to consider the attributes, ingredients or features of a brand to evaluate benefits, which would produce larger attribute→benefit loadings.

By not constraining the brand→benefit loadings to be equal within a brand, our model more closely reflects what may be expected in the "real world," as the literature review above demonstrates. [2] From these results managers can evaluate the relative magnitudes of the *average* brand→benefit vs. average attribute→benefit loadings to gain insight into the extent to which the overall brand image versus detailed attribute-specific information contributes to brand-benefit beliefs. They also can examine the variation in the *individual* brand→benefit loadings across benefits within a single brand to understand on which benefits the brand has the most significant impact. Employing a constrained (equal) effect model would not be helpful as the estimated brand→benefit loading (which we subsequently call the "brand effect") would be the same for *any* benefit. Models that allow for differential effects are preferred if differential effects actually exist in the market, as they allow the manager to determine the impact of strategic changes (e.g., a repositioning or emphasis) over time on a particular benefit. Next we develop and test such a model.

The Model

A key issue in model specification is the correlations between latent brand and attribute sources. Since brand and attribute sources have been shown to be distinct, they are uncorrelated in the model. The correlations within each source (brand and attribute), however, can vary. With regards to attribute sources, all product attributes potentially are related due to their common relationship with many brands in the same category and thus attribute sources should be correlated. In this manner, each latent attribute source (bottom oval) represents the specific *portion* of a respondent's mental network that includes the attribute node(s) related to the benefit in question. The attribute source cannot contain all brand/category information, as it would then subsume the brand source. Instead, it contains only the relevant nodes for evaluating the focal benefit. Moreover, the sets of nodes represented by each attribute source may be overlapping; that is, attribute nodes that are relevant for evaluating a benefit may be related to more than one benefit (e.g., engine size [attribute] is conceptually related to *both* sportiness and acceleration [benefits]).

Brand sources, on the other hand, are not correlated initially as brands are expected to develop unique identities. It is rare that the most prominent overall association tied to one brand (e.g., "overnight" for FedEx) is related to the most prominent overall association tied to another (e.g., "Logistics" for UPS). If this were not the case, it would suggest poor branding and positioning execution. (We address this proposition subsequently as an empirical question in an extended version of the decompositional model to see if expected correlations among brands [e.g., brands within the same brand family] can be identified in actual product market settings.)

Model Estimation

The proposed model is estimated through a model similar to the standard CFA form:

(1) $$\Sigma = \Lambda_B \Phi_B \Lambda'_B + \Lambda_A \Phi_A \Lambda'_A + \Psi,$$

where Σ is the ab × ab correlation matrix of brand beliefs for a attributes and b brands, Λ_B is the brand source loading matrix (Λ_A for attributes), Φ_B is the brand source correlation matrix (Φ_A for attributes), and Ψ is the random error component (unique variances in factor analysis). The distinction from a standard CFA model is that brand and attribute sources are distinct (i.e., not correlated) to allow for different relationships among brands or attributes. The brand source correlation matrix Φ_B is an identity matrix that implies uncorrelated brands, while the attribute source correlation matrix Φ_A allows for correlations among attributes. The estimation procedure provides the parameter values for the paths between the brand or attribute sources (ovals) and the consumer brand-benefit beliefs (rectangles), that is, brand→benefit loadings (β) and attribute→benefit loadings (α) as shown in Figure 1.

EMPIRICAL APPLICATION

We next apply our model to consumer data to determine the extent of equal versus differential brand effects within real brands in actual product-markets. The following section reports results using consumer survey data for more than 55 brands across nine markets in four countries.

Data Source

Data were provided by a large consumer packaged goods (CPG) company that has developed a brand equity measure based on Keller's (2008) Consumer-Based Brand Equity

(CBBE) framework. (Keller's model was created prior to its 2008 publication and was used by our CPG firm to develop the survey.) We use our model to analyze consumer brand beliefs data for all major brands in four categories—oral care, skin care, and two paper products categories—across four countries: the United States, United Kingdom, Germany, and China. The data were collected during 2002-2004 as part of the company's ongoing brand tracking. While data for all categories were not available for all countries, the total data set did include nine product-markets (country–category combinations) consisting of responses from between 311 and 991 consumers ($\bar{n}$ = 614) and five to nine brands. We analyze up to 10 of the most-important benefits from the CBBE "performance" box in each market. In Keller's framework, performance questions are at the lowest level and reflect how consumers evaluate the actual performance of a branded offering, as opposed to judgments or feelings about it or images connected to it.

We chose to focus on the "performance" questions because these are the most managerially actionable. Although for confidentiality reasons we are not able to reveal the actual questions, benefits that are representative of the "performance" box of a category such as "surface cleaning" are: cleans well; cleans quickly; is reliable; requires less scrubbing; is strong; is effective; is long-lasting; is natural. Importance of benefits was measured by the firm based on each benefit's contribution to the overall brand evaluation. Data were collected in a "pick any" format. Respondents were asked to check all brands that they felt "cleans well," or "cleans quickly," "is strong," etc.

Model Estimation and Stability

Although our model avoids the potential correlated brand sources problem identified by Marsh (1989), issues may still remain when the model is applied to small cases/situations where such specifications have inherent problems due to their dimensionality (Kenny, 1979). We note that prior uses of similar models (e.g., multi-trait multi-method [MMTM] models) suffer from small numbers of traits and/or methods: 3 traits and 3 methods in Bagozzi & Yi (1993); 3 methods and 2 traits in Bollen & Paxton (1998); 2 methods and 3 traits in Kumar & Dillon (1992). Anderson & Rubin (1956) and Shapiro (1985) suggest that if a model of this type has four or more brands and four or more benefits, the solution will almost always be unique. In addition, "with large sample sizes, random errors of measurement, and a correctly specified model, a CFA model will, for all intents and purposes, provide a perfect fit" (Dillon, et al., 2001, p. 420). Our analysis avoids issues of stability as it includes at least five brands (as many as nine) and at least seven benefits in each product market with sample sizes no smaller than 311 (average sample size of 614).

Sequence of Steps Used to Apply the Procedure

The example below demonstrates the procedure using five brand-benefit ratings for four brands. For illustration purposes, four brands were selected from the market, representing a mixture of global, national and store brands, along with five benefits for each brand. Although for confidentiality reasons the actual benefits or brands cannot be revealed, the following list is typical of the benefits found in this type of product category: *absorbent*, *cleans*, *gentle*, *lasts long*, *soft*, *strong*, *doesn't tear*. Surveys would ask respondents whether or to what extent a particular set of brands provides these benefits.

Step 1: Identification of Brands and Benefits. As noted earlier, there should be at least four brands and four benefits. From the available data, we examine a model incorporating four brands and five benefits to illustrate the actual procedure. In this example, the five benefits selected are among the ten most-important benefits based on proprietary importance criteria for the product category.

Step2: Data Collection of Brand-Benefit Ratings. In this step the individual ratings of benefits for each brand are collected and a covariance/correlation matrix is prepared as input for the estimation process. In this example, 20 ratings were obtained from each respondent indicating whether or not each of the four brands exhibited the five benefits (n=418). Apply a procedure appropriate for the respondent data to produce a correlation matrix for input in model estimation. For example, Pearson correlation is appropriate for Likert-type data. A Polychoric correlation or procedure such as that introduced by Edwards and Allenby (2003) may be appropriate for binary (i.e., pick-any) type data. Table 1 provides the correlation matrix for the U.K. Paper Products Market data.

[Insert Table 1 Here]

Step 3: Model Estimation. We model one latent brand source for each brand in the dataset and one latent attribute source, along with an error term, for each benefit in the dataset. Brands remain uncorrelated, while correlations among all attributes are estimated. Variances for both latent brand and attribute sources are set to 1.0. For the constrained model, estimate a single brand→benefit loading for all brand-benefit loadings within a brand. For the unconstrained model, estimate separate single brand→benefit loading for all brand-benefit loadings within a brand. Using AMOS, LISREL or any comparable SEM program, estimate models based on the theoretical assumptions described above and the structure of the data (i.e., number of brands and benefits).

Step 4: Interpretation of the results. The first task is to assess the overall model fit. A wide array of fit indices is available for SEM models. In this example, all model fit measures were within acceptable ranges for both models (Table 2). Next, we proceed to (1) evaluation of the presence of differential versus equal brand effects and then (2) interpretation of the parameter estimates at both the overall and individual effect levels.

[Insert Table 2 Here]

In addition to the overall model tests, the amount of variance explained for each benefit should be examined to ensure that an acceptable level of explanation was achieved. In the case of the differential effects model, the amount of variance explained ranged from .805 to .534, with an average of .675. Thus we can see that for all benefits at least over half of the variance was explained and on average about two-thirds could be attributed to either the brand or attribute effects.

Testing for Differential Effects. Testing the assumption of a constrained effects model (i.e., all brand effects are constant within brand) involves a test of the overall model and then tests for each brand separately. In the overall model test, the constrained effects model is compared with a nested model comparison to a differential effects model, where the brand effects are allowed to vary within brand. A significant chi-square difference indicates that a differential effects model does improve model fit and thus the assumption of constrained effects is inappropriate. The actual results from analysis of this complete dataset are presented in the next section.

RESULTS

Using the procedure outlined above, the following section examines results from a single representative product market to identify brands with equal versus differential effects within brands. Focus then shifts to model results across all nine product markets, with particular interest in the differential versus equal brand effects within brands in each product market.

Testing the Assumption of Equality of the Brand Effect

The issue of equality of the brand effect is testable by constraining the brand→benefit loadings for all brands to be equal across benefits within a brand (i.e., $\beta_1 = \beta_2 = \beta_3 = \ldots = \beta_n$) and then comparing model fit to that of an unconstrained model. This direct test for differential brand effects can be applied to the overall model as well as each brand individually. An example of this approach with data from a U.K. Paper Product market is shown in Table 3, which presents results of the overall model test as well as results for four of the six brands in the market. The two other brands in this market (one equal and one differential effect) were not shown here for presentation purposes, but exhibit the same patterns as those shown. Several observations can be made. First, the overall model test indicates that differential effects are present ($\Delta\chi^2 = 121.5$, 42 *df*, $p = .000$). This is supported when individual brands are examined, as half of the brands in this market (brands 1 & 3, Table 3) have differential effects. Examination of the brand effect values in Table 3 reveals a visibly higher variation in values for those brands with differential effects compared to those determined to have equal effects. It should be noted that the type of brand effect (equal or differential) is not dependent on the general (or average) level of the brand effects. One of the brands with equal effects (Brand 2) has the highest level of brand effects, yet the other brand with equal effects (Brand 4) has brand effect levels comparable to those with differential effects. Also, differential brand effects can be found both when the overall brand effect levels are higher (Brand 3) or lower (Brand 1) than the attribute effects. Examination of this and other markets supports the finding that type of brand effect (equal or differential) is not related to the level of the brand effect. Finally, the attribute effects associated with all brands are differential, which is expected, as consumer product/category knowledge of attributes that give rise to these benefits is likely to vary across the set of brands and benefits.

[Insert Table 3 here]

The results suggest that a constrained model with the assumption of equal brand effects causes significant distortions in the estimated brand effects and poorly captures the differential effect of the brand source on consumer brand-benefit beliefs. The more flexible structure of our model (allowing for separately estimated β_{ij}) is appropriate because overall brand impressions or positioning may be related only to particular brand-benefits and not uniformly impact benefits that are unrelated to a brand's reputation or positioning.

Evaluation of Nine Global Markets

As noted previously, the model is applied to nine global markets to determine the extent of differential effects within brands. Table 4 contains the characteristics of each market (number of brands and benefits analyzed), the overall model test for presence of differential effects, the model fit results for the differential effects model, and finally the number of brands with equal or differential effects. All of the models have fit statistic values well within acceptable ranges, as expected, allowing us to examine the tests for differential effects with confidence that the model is capturing the two types of effects (brand versus attribute) successfully.

[Insert Table 4 here]

Examination of results from the nine markets shows almost every combination of brand effects. First, the overall model tests show that differential effects exist in eight of the nine markets. This is supported when individual brands in each market are examined, as the market showing no difference in the overall market test (UK skin Care) also has no brands with differential effects. For the markets containing brands with differential effects, two markets (China Oral Care and Germany Paper Product 2) have only brands with differential effects, while the other six markets show a mixture of brands with equal and differential effects. But in all of these markets, at least half of the brands have differential effects. These results illustrate the need to remove the assumption of equal brand effects to accurately estimate the effects of "brand" across a range of benefits and markets.

While it is beyond the scope of this paper to provide an explanation for why differential effects or equal effects exist in particular markets for particular brands, as the diversity of categories and global markets could suggest many possible reasons, we note that the selection of benefits likely has a significant impact. Because we chose the most important benefits in each product category, it is possible that in some markets none of the benefits we analyze are determinate. That is, because they are all "important" they all may be required. It is possible that for the brands where we find no differential brand effects, those brands are positioned on other benefits, or lack a strong position in consumers' minds. But our approach highlights this issue and allows the brand manager to determine whether this result is troubling or expected.

While we have demonstrated the need to accommodate potential differential brand effects, an extension to our model can provide face validity for the claim that the brand→benefit loadings actually represent a brand effect. One product market (U.S. Paper Product 1) has offerings that can be separated by brand family (e.g., Kleenex Cottonnelle, Kleenex Cottonnelle Ultra, Kleenex Cottonnelle with Aloe and Vitamin E, plus multiple offerings under the Charmin brand). These relationships should be reflected in correlated brand sources, which can be identified with an extension to our base model. When the model is estimated with correlated brands, the result is a very accurate depiction of the brand structure within the market (see Table 5). Applying principal components analysis with oblique rotation to the correlations among brands results in three factors, each correctly representing a separate brand family. Moreover, the correlations between factors (i.e., brand families) are minimal (all less than .14). This supports one of the basic tenets of family branding: developing a strong, shared image that is distinct from that of other family brands. It also provides validity to the claim that our brand→benefit loadings actually capture a brand effect.

[Insert Table 5 here]

Use of Brand vs. Attribute Sources to Evaluate Brand Benefits

The approach we have described can help brand managers determine the overall relative use of the brand bucket vs. the attribute bucket when the average brand→benefit loading is compared with the average attribute→benefit loading for a particular brand across markets, which may be particularly useful for brands that have a global reach. But it also is useful to compare brands within the same market.

For example, we found that the leading brand in the U.K. skin care market in 2002 had nearly three times the share of its next competitor. Thus, we investigated whether consumers who used the leading brand relied on different mental sources to provide their brand beliefs than did those that did not use the leading brand. Indeed, we found that consumers who used the leading brand relied more on the brand bucket (i.e., larger average brand→benefit loadings), whereas those who did not use that brand relied more on the attribute bucket (i.e., larger average attribute→benefit loadings). This result suggests that consumers who did not purchase the leading brand may have had specific reasons for their decision. When presented with the results, managers at the CPG company that supplied the data suggested that based on the category in question, some consumers preferred other brands for reasons such as allergies or skin type and therefore may draw on detailed attribute information (i.e., ingredients) about the brands when they provide their brand beliefs.

We have also found differences by age. In the same U.K. Skin Care market we found that younger consumers evaluated the #3 brand more on attribute sources than did more mature consumers. These differences persisted over time, as we were able to compare results of the same analysis on 2004 U.K. Skin Care data. Thus, it is clear that evaluating the relative use of the brand vs. attribute bucket can provide meaningful insights for brand managers that want to understand the relative importance of brand vs. attribute information in consumer evaluations.

GENERAL DISCUSSION

We acknowledge that brands have strong and broad effects across a variety of benefits and stakeholders. But our research indicates that they are not blunt instruments. Rather, brands have a differential effect on the evaluation of specific benefits. This paper offers a methodology and evidence of its ability to see consumers' use of the different informational "buckets" within and across benefits for a brand. With this information, managers are able to determine if their branding, positioning and/or messaging is having the desired impact on consumer evaluations and can make and evaluate required changes.

Summary of Findings and Managerial Contributions

The ability to decompose consumer brand beliefs into overall brand and detailed attribute-specific sources provides managers with insights into which latent mental sources consumers use to construct their brand beliefs. A significant contribution of this research is the finding that many times the brand source differentially impacts consumers' evaluations of brand-benefits, a finding that is contrary to the assumption of a consistent halo effect, which has important managerial implications for segmentation, positioning, communications strategies and marketing research. As such, the methodology provides useful descriptive and diagnostic measures concerning the sources of suspicious, interesting, or worrisome consumer brand beliefs as well as a means of investigating the efficacy of branding campaigns, whether they be based on building consistency across all brand benefits or a differentiation among benefits of the brand.

The extension of the model to assess the relationships between brands provides direct evidence of brand structure within a market and insights into the effectiveness of family brand strategies. These relationships could also be used in multidimensional scaling analyses to define relative positions of brands. Importantly, they provide evidence of the validity of the results from the decompositional model to capture brand effects.

Limitations

Two aspects of the estimation procedure suggest caution with this approach. The first involves the need for a fairly large set of brands (minimum of 4 or 5) and a similar number of benefits. Although this may not be a concern for companies that routinely collect data on many or all brands competing in a category, it does preclude use of the model in situations where such extensive data collection does not exist (e.g., targeted surveys covering only two brands).

A complementary issue is interdependence between the elements of the attribute source. As benefits become highly correlated, estimation of the corresponding attribute sources may become problematic, resulting in indeterminate or improper solutions. This can occur when identical surveys are used across countries, as was the case with our data. In such cases, benefits which are highly distinct in one country may be less so in others, resulting in high intercorrelations. Although any form of *post hoc* data reduction or development of composite measures among benefits would to some degree reduce the clarity or actionability of the results, researchers may still find they need to carefully consider the set of benefits used in the analysis to ensure that the benefits are fairly distinct in nature. Ultimately, such considerations should influence survey design in terms of the benefits included. In our experience, we found it necessary to exclude some benefits in certain markets to produce a proper solution, which may limit comparability across markets.

Implications and Further Research

Even with these limitations, we are able to conclude that brand effects are not the only sources consumers use to evaluate brand benefits; neither are they uniform across benefits. More specifically, we demonstrate with 55 brands across nine markets in four countries that (1) differential brand effects exist in brands in numerous global product-markets and exist simultaneously in combination with brands with equal effects; (2) our model can be extended to portray the relationships among brands to reveal market-level brand structure; and we demonstrate in seven brands across two countries that (3) it is possible to determine consumers' relative use of overall brand information versus detailed attribute-specific information within and across benefits.

It is now possible to evaluate the differential effects of "brand" and track consumers' varying reliance on brand versus attribute sources. The major implication of this research is that researchers should no longer rely on models with a single variable intended to capture a uniform or equal effect of "brand;" instead, future models should accommodate differential effects. With such models, researchers and managers are better equipped to approach segmentation, positioning, brand communications and market research.

Segmentation implications. An implication of our research is that "primary source of brand-benefit belief" may be an important segment characteristic. Analysis of brand and attribute loadings by benefit can be used to identify, and more fully understand, important differences between existing segments of the market. Further, within existing segments, it may be possible to identify differences in sources of brand beliefs between new vs. experienced users, heavy vs. light users, younger vs. older consumers, more vs. less wealthy, etc. Relative to others, these individuals may develop their brand beliefs differently and could be identified as important sub-segments. We demonstrated a few of these effects previously in the U.K. skin care market.

Positioning implications. The approach described in this paper can be used to identify which brands "own" particular benefits, making it harder for other brands to also position on those benefits. Although it is possible for multiple brands to be perceived to deliver a benefit, an implication of this research is that the brand with a significantly higher brand→benefit loading and significantly lower attribute→benefit loading than all other brands on a benefit owns that benefit and has an advantage in consideration and choice (see Volvo and "safety" and interference described previously). However, analysis may reveal that no brand owns a particular benefit, making it possible for a brand to (re)position on that benefit. Additionally, when a brand does own a benefit, the best approach to compete on that benefit is to emphasize the low-level attributes, ingredients or features that give rise to the benefit and not to try to connect the brand with the benefit at a higher brand level.

Brand communication implications. After segment and sub-segment differences and brand positions are identified, communications strategies can be developed based on target consumers' use of either high-level brand or low-level attribute information. The implication is that a mismatch between the level of information communicated by a brand and the source of information that consumers rely on will result in less effective communication, especially when one brand owns a particular benefit (as characterized previously) and another brand tries to develop a direct higher-level association with the benefit at the brand level. In such cases, it would be more effective to communicate lower-level attribute information.

Marketing research implications. We chose to focus on the 10 most important performance benefits as identified by our CPG company, but a major implication of our research is that the results depend heavily on the brands and benefits included in the questionnaire. Thus, researchers should be careful when trying to apply our approach to existing data. Not only do stability issues arise when fewer than four brands are analyzed, but the results are not complete if not all brands in a category are included in the dataset. The implication is that tracking studies that focus on all brands and all important benefits should be conducted at an interval sufficient to detect meaningful changes. The good news is that the questionnaire for such tracking studies does not have to be extensive. Pick-any tasks such as those used to collect our data can produce sufficient responses without taxing respondents. For example, it should be possible to easily field a quarterly tracking study of 500 consumers responding to 10-15 benefits related to 4-10 brands in a category with low cost and low risk of respondent fatigue.

Further research. We have demonstrated the benefits of analyzing consumer brand beliefs survey data with cross-sectional data, and we now suggest that the model should be sensitive enough to pick up changes in consumers' use of the two sources over time. Thus, future studies that analyze longitudinal data would demonstrate the ongoing usefulness of the model as a brand-tracking tool. With such data, the proposed procedure should be helpful for diagnosing the efficacy of an advertising campaign, repositioning, repackaging, or new product entry under an existing brand name. Brand managers currently have no short-term way of knowing whether their brand-building activities are working. By observing the sources of brand beliefs before and after a strategic change, managers would be able to tell whether consumers were focusing more on specific attributes or the overall brand to provide their beliefs.

Although the procedure should work in such an application, further research might seek to determine how quickly such strategic activities can affect the sources of consumer brand beliefs. The brand→benefit or attribute→benefit loadings may change before either raw consumer brand beliefs or aggregate market-level measures, such as market share or loyalty, but this hypothesis should be confirmed. Additionally, our theorizing suggests that since a brand is closely tied to its promise of benefits (Raggio & Leone, 2007), it should have a greater impact on those benefits that are directly related to its promise. If not, this would suggest either poor communication of the brand's promise, or a deficiency in meeting it. Calculating brand→benefit loadings for specific brands and benefits and matching them with their associated positioning, would allow researchers to test this hypothesis.

ENDNOTES

[1] See, e.g., Gilbride, Yang and Allenby (2005), equation (3), p. 314: $x^*_{hij}=\alpha_{ij} + \delta y_{hi} + \varepsilon_{hij}$, where x^*_{hij} represents brand beliefs x for a particular household h for a particular brand i and benefit j, α represents the common perception of the level of benefit j for brand i, and ε is an individual error term. δy_{hi} reflects the justification bias for a particular household h for brand i. Notice that this bias is consistent across all benefits within a brand, as j is not included as a subscript.

[2] Of course, the attributes also should not be constrained, since not all brands might be viewed as equally strong on specific attribute→benefit linkages and therefore these values should not be constrained to be equal. For example, for sports drinks the benefit of 'provides energy' would be much stronger for a brand that is high in caffeine, ginseng and guarana (attributes) vs. a brand that is not (and is low in sugar or calories).

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