Measuring brand value with scanner data *

Wagner A. Kamakura a
and Gary J. Russell b

a University of Pittsburgh, Katz Graduate School of Business,
Pittsburgh, PA 15260, USA
b Owen Graduate School of Management, Vanderbilt University,
Nashville, TN 37203, USA

Received August 1990; final version received September 1992

Using actual consumer choice data from a single-source scanner panel, we construct two measures of brand value which capture different aspects of brand equity. Brand Value measures perceived quality, the value assigned by consumers to the brand, after discounting for current price and recent advertising exposures. Brand Intangible Value isolates the component of brand value which cannot be directly attributed to the physical product, thus measuring the value created by such factors as brand name associations and perceptual distortions. We illustrate these measures in a study of the powder laundry detergent category and briefly relate the results to strategic variables (order of entry and cumulative advertising expenditures).

Introduction

What is the value of a brand? How can it be assessed? The search for answers to these questions has gained prominence both in academia and industry, due to the growing recognition of brands as valuable assets for the firm. From a product policy perspective, brand value (or equity) is the outcome of long-term investments designed to build a sustainable, differential advantage relative to competitors (Doyle, 1990). However, little consensus has emerged about how brand equity should be measured.

The reason for this lack of consensus is that brand value may be defined in a variety of ways. In general, either of two perspectives may be adopted: the value of the brand to the firm, or the value of the brand to consumers.

Brand equity as the value of the brand to the firm

Many researchers view brand equity from a financial perspective, based on costs (Stobart, 1989), present and future earnings (Brasco, 1988), incremental cash flows relative to unbranded goods (Simon and Sullivan, 1990) or a comparison of the brand characteristics with those of representative (usually unbranded) competitors (Wentz, 1989). The main purpose under this perspective has been on the valuation of brands as intangible assets to be included in the firm's published financial statements (Barwise et al., 1990).

One of the most elaborate of such procedures is that of the Interbrand group, a London-based consulting firm. Interbrand multiplies average profitability over the past three years by a P/E (price/earnings) multiplier. This P/E multiplier is estimated as a function of a “brand strength index” composed of subjective ratings of the brand on market leadership, brand stability, international presence, long-term trend and stability of the product category, trademark protection, and advertising and promotion support (Penrose, 1989).

Correspondence to: Professor G.J. Russell, Owen Graduate School of Management, Vanderbilt University, Nashville, TN 37203, USA.

* The authors thank A.C. Nielsen for providing the scanner data analyzed in this study and gratefully acknowledge research funding from the Marketing Science Institute. The authors also wish to thank Mitzi Miller for able research assistance. Authors' names are listed in alphabetical order. Both contributed equally to the research.

North-Holland

0167-8116/93/$06.00 © 1993 – Elsevier Science Publishers B.V. All rights reserved
Another way of assessing the value for the firm is through the brand’s ability to maintain a long-run competitive advantage (Blackett, 1989, Murphy, 1989). Blattberg and Wisniewski (1989) provide evidence that higher-priced brands, which are often perceived to be of higher quality, are relatively less vulnerable to competitive price cuts than are lower-priced brands. Moran (cited in Yovovich, 1988) argues more generally that differences in cross price elasticities reflect differences in brand equity.

Brand equity as the value of the brand to the consumer

Brand equity can also be viewed as the contribution of branding to the physical product. According to Nagle (1979), a brand name represents a collection of concepts which consumers learn to associate with a particular product. These concepts are studied by eliciting consumers’ free associations in response to a brand name (Tauber, 1981).

The nature of these associations is of considerable interest to managers contemplating the extension of a brand name across several products. Aaker and Keller (1990) argue that consumers are more likely to accept a brand extension when there is a perceived fit in terms of product complementarity or common attributes. For example, when developing its now popular brand of spaghetti sauce, Campbell’s chose not to use its familiar trademark because the sauce would be associated with “red, orangy and runny, like our soup,” according to the company’s president (Schlossberg, 1990).

Other researchers directly measure the utility or value that consumers attach to brand names. This has been done in a conjoint analysis context, in which consumers rate combinations of product features and brand names (Louviere and Johnson, 1988, Yovovich, 1988, Sharkey, 1989). The revealed preferences are then decomposed into the utility associated with the product features and the value attached to the brand names. Previous attempts to measure a brand’s value to consumers (including the ones cited above) have been based on self-reported measures of attitudes or preferences obtained through market surveys, rather than actual consumer behavior observed in the market place.

Our approach

The approach proposed in our study follows this second perspective to brand equity, measuring the implied utility or value assigned to a brand by consumers. However, in contrast to previous attempts to measure a brand’s value to consumers, our approach is based on the actual purchase behavior observed under regular market conditions. We use data on the observed purchase behavior measured by supermarket check-out scanners to estimate the value assigned by consumers to each brand in a product category, after accounting for differences in net price, and brand salience due to short-term advertising exposures. We also identify two major sources of brand equity, by decomposing brand value into tangible and intangible components. We illustrate our approach by estimating these measures of brand value in a study of the powder laundry detergent product category.

A conceptual model of consumer choice

In order to measure a brand’s value to consumers, we must understand how consumer preferences are formed and how preferences affect brand choice. For this purpose, we adopt a conceptual model of consumer choice discussed by Tybout and Hauser (1981) and Hauser (1984). Following this conceptual model (shown in Fig. 1), we assume that perceptions regarding a particular brand are formed in response to the
physical product and psychosocial cues (such as advertising messages). Consumers then make preference valuations based on brand perceptions and their motivations. Differences in motivations lead consumers to seek different benefits within a product category, thus affecting how perceptions are translated into preferences. Actual choices reflect the influences of both consumer preferences and situational constraints such as price, promotions etc.

This conceptual model is used here as a representation of important influences on consumer behavior – not a detailed description of the actual choice process at each choice occasion. We do not expect that consumers will react to their perceptions of the available brands and process that information at each choice occasion, as in traditional high-involvement choice models. Rather, we assume that throughout their repeated experiences with the product category, consumers form their own perceptions of the available brands. These perceptions, in turn, contribute to the overall value consumers assign to each brand.

Although the level of consumer involvement may decline over time (and consequently, the formal description of the choice process may change), we assume that choice always involves an attempt to maximize utility, and that utility is influenced by consumer tastes, product attributes, and psychosocial cues. Our model does not preclude the possibility that feedback from previous consumption experience and social interaction plays a role in choice (Mowen, 1988). Rather, we make the weaker assumption that these types of choice dynamics played a significantly more important role as the consumer learned about the product category and defined his brand preferences. Once these preferences have stabilized, we assume that choice can be modeled as if each consumer has a set of brand-specific utilities which are related to the factors shown in Fig. 1.

**Consumer choice model**

To operationalize the model, we adopt a random utility framework (see, e.g., Kamakura and Russell, 1989). We decompose the underlying utility of a brand into two elements: (a) a component of utility intrinsic to the brand, and (b) a component of utility which can be explained by situational factors such as price and short-term advertising exposure. Formally, when making a choice, consumer $k$ (belonging to segment $s$) assigns a random utility to each brand $j$ and chooses the brand with the highest utility on that purchase occasion. This utility is modelled as

$$U_{kj} = \alpha_{sj} + \beta_s p_{kj} + \tau_s a_{kj} + e_{kj},$$

where

- $\alpha_{sj}$ = component of utility intrinsic to brand $j$ and segment $s$ (to be estimated),
- $p_{kj}$ = net price (after promotional discounts) of brand $j$ available to consumer $k$,
- $a_{kj}$ = consumer $k$’s short-term exposure to the advertisements of brand $j$,
- $\beta_s$ = price sensitivity parameter of segment $s$ (to be estimated),
\( \tau_s = \) advertising sensitivity parameter of segment \( s \) (to be estimated), and 
\( e_{kj} = \) random disturbance with mean zero.

The intrinsic utility \( \alpha_{sj} \) represents the consumer's value for brand \( j \), after the effect of the situational factors (price, promotion etc.) have been taken into account. This value reflects the confluence of consumer perceptions and needs. By including short-run advertising in the utility equation, we allow brand choice to be affected by the increased brand salience caused by recent advertising exposure. Thus, short-term advertising exposure is treated as one of the situational factors, along with short-term price. Long-term price and advertising effects, on the other hand, are implicitly incorporated into the intrinsic value \( \alpha_{sj} \), as suggested by Fig. 1.

**Relating utility to brand choice**

If the usual assumption of independent extreme-value distributed errors is added to equation (1), the probability that consumer \( k \) chooses brand \( j \), conditional on the assumption that the consumer belongs to segment \( s \), is given by the multinomial logit model

\[
P_j(k \in s) = \frac{\exp(u_{kj,s})}{\sum_j \exp(u_{kj,j})}. \tag{2}
\]

It is important to understand that equation (2) does not imply the well-known independence of irrelevant alternatives (IIA) assumption at the market level (Ben-Akiva and Lerman, 1985). Rather, we only assume IIA within each group of relatively homogeneous consumers. The identification of these homogeneous groups of consumers and estimation of the model parameters using scanner data will be discussed later.

**Brand Value (BV)**

Since the intrinsic utility for brand \( j \) within segment \( s \) \((\alpha_{sj})\) represents the value assigned to the brand by that particular segment after adjusting for situational factors (short-term price and recent advertising), this parameter may be viewed as a measure of the brand's value within that segment. To obtain an aggregate measure, we define Brand Value (BV) as the market-wide average intrinsic utility \(^{1}\)

\[
BV_j = \sum_s f_s \alpha_{sj}, \tag{3}
\]

where \( f_s \) is the relative size of segment \( s \). BV is scaled so that the mean value for all brands in the market is zero.

A rank order of brands in terms of BV is not necessarily the same as a rank order of brands in terms of market share. According to equation (1), a brand could obtain high share either from high value or from low price. Because BV adjusts for differences in price across all products, a brand which obtains high share solely because of low price will have a lower BV than a brand which obtains high share at a high price. In this way, BV reveals the extent to which the observed market share is determined by the product's perceived quality.

**Decomposing Brand Value**

According to the consumer model in Fig. 1, the perceptions of a brand's attributes are related both to characteristics of the physical product and to psychosocial cues. Consequently, the overall value assigned to a brand can be decomposed into these two factors.

**Attribute perceptions**

Let \( Y_{sjq} \) be the attribute perception for brand \( j \) on attribute \( q \) \((q = 1, 2, \ldots, Q)\) for a

\(^{1}\) It may be argued that value should be defined as \( \Sigma_s f_s [\alpha_{sj} / |\beta_s|] \) where \( |\beta_s| \) is a scaling factor which adjusts for inter-segment differences in the variance of the stochastic error in the utility equation (cf. Srinivasan, 1979). We prefer the definition in equation (3) because \( \exp(BV_j) \) is then proportional to the geometric mean of the price-adjusted segment market shares \( \exp(\alpha_{sj}) / \Sigma_j \exp(\alpha_{sj}) \).
consumer in segment \( s \). Suppose that these perceptions are related to brand \( j \)'s actual physical features \( X_{jr} \) \( (r = 1,2,\ldots,R) \) as

\[
Y_{sij} = \sum_r w_{srq} X_{jr} + \epsilon_{sij},
\]

where the \( w_{srq} \) are coefficients that map the \( R \) physical features of brand \( j \) into its perceived attributes in a \( Q \)-dimensional attribute space (Hauser and Simmie, 1981), and the \( \epsilon_{sij} \) account for perceptual distortions which arise in response to the psychosocial cues. That is, consumers form perceptions based both upon a composition of physical features \( (\sum_r w_{srq} X_{jr}) \) and upon a distortion of these attributes \( (\epsilon_{sij}) \). For example, consumers might form their perception of a “grease fighting” attribute in a dishwashing detergent based upon observed performance (e.g., production of suds and amount of scrubbing needed to clean dirty pans) and upon advertising claims stating that the product has special cleaning agents.

**Brand Value decomposition**

We assume that the brand value \( \alpha_{sj} \) for each brand within a segment can then be written as

\[
\alpha_{sj} = \phi_{sj} + \sum_q \theta_{sq} Y_{sij},
\]

where \( \phi_{sj} \) captures aspects of brand value which are not contained in consumers’ attribute perceptions, and \( \theta_{sq} \) are the relative importances assigned to each perceived attribute. These importance weights reflect how members of each segment translate their perceptions of the available brands into preferences, in response to their motivations. Formulations similar to (5) can be found both in conjoint analysis (e.g., Louvierie and Johnson, 1988) and in multi-attribute utility theory (Srinivasan, 1979).

Combining equations (4) and (5), we obtain

\[
\alpha_{sj} = \phi_{sj}^* + \sum_r \delta_{sr} X_{jr},
\]

where \( \phi_{sj}^* = \phi_{sj} + \sum_q \theta_{sq} \epsilon_{sij} \) is the intangible component of the brand’s value, and \( \delta_{sr} = \sum_q \theta_{sq} w_{srq} \) are “engineering coefficients” which relate the physical features of the brand to the consumer’s valuation of the brand. Notice that the coefficients \( \delta_{sr} \) are not attribute importance weights. These coefficients translate physical features of the brand directly into the consumer’s valuation, and are formed as a combination of the attribute importance weights \( \theta_{sq} \) and the “mapping” coefficients \( w_{srq} \). As a result, equation (6) shows the decomposition of brand \( j \)'s value within segment \( s \) into a tangible component \( (\sum_r \delta_{sr} X_{jr}) \) which can be directly attributed to the physical features of the brand, and an intangible component \( (\phi_{sj}^*) \) which arises from perceptual distortions and other brand associations.

**Brand Intangible Value (BIV)**

We define Brand Intangible Value (BIV) as the component of the brand’s value that cannot be directly attributed to its physical features. Within each segment \( s \), this intangible component is measured by \( \phi_{sj}^* \), as presented in equation (6). However, to obtain a single measure for each brand, we define BIV as the market-wide average

\[
\text{BIV}_j = \sum_s f_s \phi_{sj}^*.
\]

By taking a weighted sum of equation (6) across segments, it is clear that

\[
\text{BV}_j = \text{BIV}_j + \text{BTV}_j,
\]

where \( \text{BTV}_j = \sum_s f_s [\sum_r \delta_{sr} X_{jr}] \) may be defined as the Brand Tangible Value. In other words, Brand Value (BV) can be decomposed into two parts: a tangible component (BTV) which arises from the physical features of the product, and an intangible component (BIV) which arises from perceptual distortions and other responses to psychosocial cues. This intangible component may be interpreted as the “added value” conferred upon a product by its brand.
At this point, the distinction between our measures should be clear. Brand Value (BV) is a measure of the intrinsic utility or value of a brand to consumers, while Brand Intangible Value (BIV) is a measure of the value of intangibles (brand name associations and perceptual distortions). Relative to a simple ordering of brands in terms of market share, BV adjusts for situational constraints (short-term price and recent advertising), while BIV adjusts for differences in both situational constraints and physical product features. A comparison of these measures (each computed on the basis of actual choice behavior) highlights the reasons for good or poor brand performance.

Estimation issues

The methodology used to implement this conceptual model is the clusterwise logit model introduced by Kamakura and Russell (1989). This model is designed to classify consumers into segments on the basis of long-run brand preferences and short-run responses to marketing mix variables. One utility function [such as equation (1)] is estimated for each group of homogeneous consumers.

Preference segmentation

According to the clusterwise logit model, any consumer has a prior probability \( f_s \) (to be estimated) of belonging to segment \( s \). Consequently, consumer \( k \)'s unconditional choice probability of purchasing brand \( j \) is obtained by combining the segment-level logit probabilities [from equation (2)] as

\[
P_{kj} = \sum_s f_s P_j(k \in s).
\]  

(9)

Maximum likelihood estimates of model parameters can be obtained by developing a likelihood function based upon equation (9) and analyzing the household purchase histories in a scanner data panel. Details on this approach (which represents the market as a mixture of logit models) can be found in Kamakura and Russell (1989). Estimation is carried out by first specifying the number of segments to be constructed. In practice, the researcher selects the number of segments to be included in the model by inspecting model fit via Akaike’s Information Criterion (AIC). This procedure leads to estimates of relative size \( f_s \), price and advertising sensitivities \( (\beta_s, \tau_s) \) and brand values \( \alpha_{sj} \) for each segment.

Measuring brand performance

Estimates of Brand Value are obtained directly from the preference segmentation results using the estimated parameters and equation (3). Estimation of Brand Intangible Value (BIV), however, requires additional computation as discussed next.

Measuring BIV involves decomposing intrinsic brand value

\[
\alpha_{sj} = \phi^*_{sj} + \sum_r \delta_{sr} X_{jr} \tag{10}
\]

into intangible \( (\phi^*_{sj}) \) and tangible \( (\sum_r \delta_{sr} X_{jr}) \) components. Although brand value can be easily decomposed in theory, practical implementation of equation (10) is not a simple task. The researcher must first identify a set of relevant physical features and obtain objective measures of these features. Perceptual measures should not be used, because perceptual distortions of brand attributes are defined to be part of the brand’s intangible value \( \phi^*_{sj} \) [see equation (6)]. In addition, most products in the market place possess a unique brand name and a unique bundle of physical features. Consequently, the intangible and tangible components of brand value are typically confounded, requiring additional assumptions for their identification.

To carry out this decomposition, we re-express the intrinsic brand value as

\[
\alpha_{sj} = \phi^*_{sj} + \sum_r \delta_{sr} X_{jr} + z_{sj}, \tag{11}
\]
where $\phi_j^*$ is the market-wide Brand Intangible Value and $z_{sij}$ is an aggregation error which reflects inter-segment variation. We also constrain the parameters in (11) to obey
\[
\sum_j \phi_j^* = 0
\]  
(12)
and
\[
\sum_j \phi_j^* x_{jr} = 0, \quad r = 1, 2, \ldots, R.
\]  
(13)

The first constraint (12) simply scales the mean of the BIV’s to zero over all brands. The second constraint (13) ensures that intangible component of the brand value is uncorrelated with the product’s physical features.

This second constraint does not preclude the possibility that intangible brand value might be correlated with consumers’ perceptual distortions of physical product features. As shown in equation (6), the intangible brand value for each consumer is influenced by both brand-specific associations ($\phi_{sj}$) and perceptual distortions ($\sum_q \theta_{sq} \varepsilon_{sij}$). For example, suppose that a dishwashing liquid positions itself as superior in terms of “grease fighting” ability. To the extent that consumers value “grease fighting” and the firm convinces consumers that the product works better than its actual performance would dictate, the brand’s intangible component is likely to increase in magnitude.

To estimate Brand Intangible Value ($\phi_j^*$), we use the estimates of brand intrinsic value $\alpha_{sj}$ (for each brand $j$ and segment $s$) obtained from the clusterwise logit model as dependent variables in equation (11). Parameters are inferred using weighted least squares (with weights proportional to segment size $f_j$) and imposing constraints (12)–(13). [The weights are necessary to ensure that the BIV estimates reflect an average across the market as dictated by equation (7).] This procedure yields BIV estimates which provide information on size of the typical consumer’s intangible component in a brand’s overall valuation.

**Empirical illustration**

To illustrate our approach, we apply the proposed measures of brand performance to the powder laundry detergent category in the US. Our primary goal is to compare the measures BV and BIV as alternative interpretations of brand equity. We argue that a brand’s competitive position can be easily summarized using BV, but that an understanding of the source of competitive strength requires an adjustment for objective product quality.

**Data description**

The data analyzed consist of 51 weeks of retail scanner transactions (spanning the period September 1987 through August 1988) collected by A.C. Nielsen. The data cover 3,766 purchases made by 302 households in one market. A household was selected from the panel if it made at least five purchases of laundry detergents during the 51-week period, and if at least 90% of those purchases were in the powder detergent (as opposed to liquid detergent) category.

The top seven national brands that did not contain fabric softeners were considered individually. The remaining national brands were combined into a composite National category; each of the brands classified in the “National” category had a share smaller than 1.2%. A Private Label category was also created by grouping together all private label and generic brands.

The following information was obtained for each brand at each purchase transaction:

(a) the brand chosen,
(b) net unit price (per ounce, after all price promotions) for each brand (for a package size comparable to the one actually chosen), at the time and place of purchase,
(c) each household’s television advertising exposures for each brand in the four
weeks prior to the date of purchase. The choice of four weeks is based on the typical interpurchase time, in order to capture short-term effects (i.e., brand salience).

A summary of the brands with respect to the key variables used in our analyses is presented in Table 1.

Segmentation results

In this first stage of our data analysis, we estimated the parameters of the clusterwise logit model (segment sizes \( f_s \), price and advertising sensitivities \( \beta_s \) and \( \tau_s \), and intrinsic brand values \( \alpha_{si} \)) by applying the maximum likelihood procedure discussed in Kamakura and Russell (1989) to the scanner data. It is important to understand that the results obtained in the first stage (particularly the intrinsic brand values \( \alpha_{si} \)) are not constrained to have any particular relationship to objective product features.

Analysis of our data yielded six segments. The qualitative criterion used to select the number of segments was Akaike’s Information Criterion, transformed into an adjusted rho-square. \(^2\) New segments were added to the model until the improvement in the adjusted rho-square was less than 0.01. The adjusted rho-square for the selected model was 0.414.

The segmentation results are displayed in Table 2. The top portion of this table shows the predicted choice shares for each segment [obtained by inserting each brand’s average price and advertising exposure into equations (1)–(2)]. The remainder of the table shows, price and advertising sensitivities (\( \beta_s \) and \( \tau_s \)), and relative size \( f_s \) for each segment.

Segment A represents more than half of the sample studied (52.3%), and is relatively loyal to Tide. Segments D, E and F are also relatively loyal to a single brand (National, Private Label, and Purex, respectively), while segments B and C switch among at least two brands. Overall, our results show sensitivity to price, but not to short-run (past four weeks) advertising. This is consistent with previous studies using scanner data (see, e.g., Tellis, 1987).

According to the estimates in Table 2, segment D accepts higher prices. These counter intuitive results are due to the segment’s strong preference for National, a multiple brand grouping which has a much higher price than any other powder detergent (see Table 1). Results for segments that prefer National and Private Label must be viewed with caution, because these groupings combine all other brands not individually considered in our model. In these cases, loyalty might in fact reflect switching among the brands contained in these groupings.

\(^2\) The adjusted rho-square is defined as \( \rho^2 = 1 - \frac{[LL_0 + PARM_s - LL_s]}{LL_0} \), where \( LL_0 \) is the maximum log-likelihood obtained with \( s \) segments, \( PARM_s \) is the number of parameters in the \( s \) segment model, and \( LL_s \) is the log-likelihood obtained with the naive model (i.e., all parameters set to zero).

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Laundry detergent data summary (US market)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brand</td>
<td>Price per ounce</td>
</tr>
<tr>
<td>---------</td>
<td>-----------------</td>
</tr>
<tr>
<td>Tide</td>
<td>41.5</td>
</tr>
<tr>
<td>Oxydol</td>
<td>12.9</td>
</tr>
<tr>
<td>Surf</td>
<td>12.2</td>
</tr>
<tr>
<td>Cheer</td>
<td>11.6</td>
</tr>
<tr>
<td>Purex</td>
<td>5.0</td>
</tr>
<tr>
<td>All</td>
<td>3.7</td>
</tr>
<tr>
<td>Arm&amp;Hmr</td>
<td>1.2</td>
</tr>
<tr>
<td>Natl</td>
<td>8.8</td>
</tr>
<tr>
<td>PL</td>
<td>3.2</td>
</tr>
</tbody>
</table>

Note: Market share, price and advertising exposure are based upon the Nielsen data analyzed in this study. Advertising spending estimates are obtained from the BAR/LNA Multi-Media Service (Leading National Advertisers 1981–1988). \(^a\) Year of product introduction shown in parentheses.
Table 2
Powder detergent consumer segments

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
<th>D</th>
<th>E</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tide</td>
<td>68.8</td>
<td>24.3</td>
<td>6.2</td>
<td>16.3</td>
<td>16.2</td>
<td>13.0</td>
</tr>
<tr>
<td>Oxydol</td>
<td>9.1</td>
<td>11.4</td>
<td>43.4</td>
<td>1.3</td>
<td>5.8</td>
<td>0.4</td>
</tr>
<tr>
<td>Surf</td>
<td>7.5</td>
<td>26.4</td>
<td>4.9</td>
<td>1.5</td>
<td>8.8</td>
<td>1.6</td>
</tr>
<tr>
<td>Cheer</td>
<td>9.7</td>
<td>6.1</td>
<td>44.8</td>
<td>2.8</td>
<td>1.2</td>
<td>2.4</td>
</tr>
<tr>
<td>Purex</td>
<td>1.2</td>
<td>4.0</td>
<td>–</td>
<td>4.6</td>
<td>3.0</td>
<td>78.5</td>
</tr>
<tr>
<td>All</td>
<td>1.1</td>
<td>13.1</td>
<td>0.3</td>
<td>–</td>
<td>0.6</td>
<td>1.6</td>
</tr>
<tr>
<td>Arm&amp;Hmr</td>
<td>–</td>
<td>6.0</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Natl</td>
<td>2.0</td>
<td>8.2</td>
<td>0.4</td>
<td>73.0</td>
<td>0.9</td>
<td>1.2</td>
</tr>
<tr>
<td>PL</td>
<td>0.6</td>
<td>0.6</td>
<td>–</td>
<td>0.5</td>
<td>63.5</td>
<td>1.3</td>
</tr>
<tr>
<td>Price</td>
<td>–0.79</td>
<td>–0.40</td>
<td>–0.08</td>
<td>0.20</td>
<td>–0.84</td>
<td>–1.03</td>
</tr>
<tr>
<td>Adv.</td>
<td>0.03</td>
<td>0.01</td>
<td>0.07</td>
<td>0.08</td>
<td>–0.00</td>
<td>0.04</td>
</tr>
</tbody>
</table>

Segment size (%) 52.3 22.5 10.1 6.5 4.6 4.0

* Choice shares less than 0.1 are denoted as (–). Predictions are obtained by inserting each brand’s average price and advertising into equations (1)–(2).

b Parameter statistically significant at the 0.05 level.

Measuring Brand Value

Market-wide measures of Brand Value (BV) for each brand were computed by inserting the \( \alpha_{ij} \) estimates (obtained from the preference segmentation model) into equation (3). The resulting BV\_j measures are listed in Table 3 and displayed in a plot which also gives information on average market shares and prices (Fig. 2).

The intuitive meaning of the BV measure becomes evident in Fig. 2. Brands such as Tide can attain high shares at an average price because consumers attach a high value to them. On the other hand, brands with low value such as Private Labels, Arm & Hammer and Purex have a low share of the market, despite their lower prices.

The results displayed in Fig. 2 show that high market share tends to be directly related to high brand value (compare, for example, Tide vs. Arm & Hammer). This strong market share effect (called “double jeopardy” by Ehrenberg et al., 1990) is empirically driven, rather than a direct implication of our measurement model. Figure 2 also shows a strong price effect. One can identify three groups of brands, with high (> 40%), medium (8–13%) and low (< 6%) shares. Within the two last groups, BV is more strongly related to the average price of the brand than to its share: for a given market share, Brand Value increases as price increases.

The only apparent departure from this pattern is the National grouping. This grouping attains the same level of market share as Cheer, at a higher price. Its BV is lower than Cheer, contrary to what one would expect. Notice, however, that the National grouping is an aggregate of many brands with low market shares. Each brand in this grouping

Table 3
Brand performance indices

<table>
<thead>
<tr>
<th></th>
<th>Market share</th>
<th>Brand value (BV)</th>
<th>Brand ( ^{a} ) intangible value (BIV)</th>
<th>Brand ( ^{a} ) tangible value (BTV)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tide</td>
<td>41.5</td>
<td>2.284</td>
<td>0.275</td>
<td>2.094</td>
</tr>
<tr>
<td>Oxydol</td>
<td>12.9</td>
<td>1.516</td>
<td>0.298</td>
<td>1.218</td>
</tr>
<tr>
<td>Surf</td>
<td>12.2</td>
<td>1.108</td>
<td>0.098</td>
<td>1.018</td>
</tr>
<tr>
<td>Cheer</td>
<td>11.6</td>
<td>1.262</td>
<td>1.099</td>
<td>0.163</td>
</tr>
<tr>
<td>Purex</td>
<td>5.0</td>
<td>–1.201</td>
<td>–0.112</td>
<td>–1.089</td>
</tr>
<tr>
<td>All</td>
<td>5.7</td>
<td>–1.078</td>
<td>–1.024</td>
<td>–0.054</td>
</tr>
<tr>
<td>Arm&amp;Hmr</td>
<td>1.2</td>
<td>–2.671</td>
<td>–1.514</td>
<td>–1.125</td>
</tr>
<tr>
<td>Natl</td>
<td>8.8</td>
<td>0.944</td>
<td>2.527</td>
<td>–1.583</td>
</tr>
<tr>
<td>PL</td>
<td>3.2</td>
<td>–2.164</td>
<td>–1.614</td>
<td>–0.550</td>
</tr>
</tbody>
</table>

\( ^{a} \) BV = BIV + BTV.

Note: BV, BIV and BTV are scaled to sum to zero across all brands. All BV measures are statistically different from zero.
in fact attains low share at a high price: this explains why the National grouping has a lower Brand Value.

Measuring Brand Intangible Value

In order to isolate the intangible component of the brand's value, we must identify the relevant physical features in the product category and obtain objective measurements of these features for each brand in the category. As proxies for the tangible aspects of the product, we used the performance ratings for laundry detergents published by *Consumer Reports* (February 1986 and July 1987). *Consumer Reports* used laboratory tests to rate laundry detergents on three performance dimensions (anti-redeposition, whitening and stain removal) on two types of fabric (polyester-cotton and nylon).

To simplify the analysis, we used a principal components decomposition of these six performance ratings to create three basic performance factors explaining 76% of the original variance. We labeled these factors: brightness (anti-redeposition), whiteness, and stain removal. The scores of the nine brands are displayed in Fig. 3. The scores for National and Private Label are simple averages for the brands included in these groupings for which attribute information was available.

![Brand Attributes Diagram](image_url)

Fig. 3. Brand attributes
We used the objective features shown in Fig. 3 to decompose the intrinsic values $\alpha_{s_l}$ into segment-level “engineering coefficients” $\delta_{s_l}$ (listed in Table 4) and Brand Intangible Values $\phi_k$ (listed in Table 3). As discussed earlier, Brand Intangible Value attempts to isolate the component of brand value not accounted for by the physical features. We wish to emphasize that the empirical measures of Brand Intangible Value for powder detergents presented here are conditional on the assumption that the three basic features in Fig. 3 are the most relevant objective attributes in this product category, and that evaluative perceptions are part of the intrinsic value $\alpha_{s_l}$. This assumption must be kept in mind when evaluating our BIV measures.

**Tangible vs. intangible value**

Decomposition of Brand Value into its tangible and intangible components was carried out by applying the procedure described in equations (11)–(13). We display the relationship among Brand Value (BV), Brand Intangible Value (BIV) and Brand Tangible Value (BTV) in Fig. 4. [As shown in equation (8), BTV represents the average consumer’s valuation of the brand’s objective product attributes.] Figure 4 also contains information on cumulative advertising expenditures (in millions of dollars) during the 1981–1987 period, and on the order of market entry.

The first conclusion we may draw from this figure is that overall quality perceptions as measured by BV are strongly related to consumer evaluations of physical features of the brand (as measured by Brand Tangible Value). Brands that offer desirable features (e.g., Tide) have high brand value, in contrast to brands with poor physical features (e.g., Arm & Hammer). Although this finding is not surprising, it is important because the intrinsic brand values calculated by the clusterwise logit model need not have any relationship with the objective product attributes. Thus, this relationship serves as a check of the reasonableness of the model.

The line bisecting Fig. 4 separates the brands with positive and negative values of BIV. Brands located above this line have greater brand value than expected from their measured attributes, and thus have a positive intangible value (displayed as the vertical deviation of the brand from the dividing line). Brands which are located below this line are assigned a negative intangible value; their market performance is weaker than expected on the basis of objectively measured attributes.

To gain an intuitive understanding of the difference between Brand Value and Brand Intangible Value, it is useful to compare Cheer and All. Although Cheer and All have very similar objective attributes (Fig. 3), Cheer has a much larger share (11.6%) than All (3.7%), despite its higher price (3.93 vs.

---

**Table 4**

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Coefficient estimates within segment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>A</td>
</tr>
<tr>
<td>Stain removal</td>
<td>0.26</td>
</tr>
<tr>
<td>White</td>
<td>0.52</td>
</tr>
<tr>
<td>Bright</td>
<td>1.60</td>
</tr>
</tbody>
</table>

*a* Parameter statistically significant at the 0.05 level.
2.57). For this reason, Figure 4 shows similar Brand Tangible Values for both brands, but radically different Brand Values. The result is that Cheer is assigned high intangible value (a positive deviation from the bisecting line), while All is assigned low BIV (a negative deviation from the bisecting line).

Although high BIV in general contributes to high BV, brands with high value need not have high intangible value. A clear example is Tide. Although Tide possesses a positive BIV, its overall value is very close to what we would expect from its objective attributes. Managerially, this suggests that the value of the Tide brand is primarily based upon its excellent product performance (see Fig. 3).

Correlates of brand equity

Although our study is not centered on the sources of brand equity, we consider some anecdotal evidence on the relationship between our brand valuation measures and two strategy variables: order of entry and cumulative advertising expenditures (listed next to each brand in Fig. 4). Order of entry shows the strongest relationship. All brands with a positive BIV are early entrants in the market, while late entrants have negative BIV’s. Early entrants also have the highest BV’s while late entrants have some of the lowest. The only exception is the National grouping of several brands with marginal shares, for which we have little information.

Most brands with positive BIV are also the ones with the highest cumulative advertising in the category. The notable exception is All, with a large ($79.9 million) cumulative expenditure and a low intangible value relative to other brands with lower investments in advertising. This exception is important because it underscores the notion that a large investment in advertising does not necessarily translate into market success. As we showed in Table 2, All is not the most desired brand in any consumer segment, despite the considerable advertising expenditure.

Clearly, these results must be viewed cautiously. We must emphasize that our measure of intangible value (BIV) is a residual, and is conditional on both the validity of the overall BV measure and on the particular objective measures of physical features used. In contrast, BV is not dependent on knowledge of these physical features.

Conclusions

We propose behaviorally based measures of brand valuation which view brand equity from different stages of the consumer decision process. Although other researchers have attempted to measure brand value to the consumer, these previous measures have been based upon self-reported attitudes and preferences obtained through surveys and conjoint tasks. In contrast, our approach provides a measure of consumer value based upon actual choice behavior in the market place.

Brand Value (BV) is a measure of the intrinsic utility or value of a brand to consumers, after adjusting for situational factors. This measure is derived from a probabilistic choice model following the classical assumptions of random utility theory. In an application to the US powdered detergent market, we measured BV using short-term price and recent advertising as situational factors. We found that price is an important situational influence on choice; in contrast, increased salience due to recent advertising exposure had no measurable impact. Comparing across brands, we showed that high Brand Value scores correspond to brands which maintain high market share at a high price. Although this type of relationship is intuitively reasonable, the specific functional relationship found in our study (Fig. 2) is a reflection of
our data and is not dictated by the model formulation.

Because Brand Value reflects the utility assigned to the extended product, it contains both tangible and intangible components. Brand Intangible Value (BIV) is a measure of the utility associated with intangible factors such as brand name associations and perceptual distortions. Relative to a simple ordering of brands in terms of market share, BV adjusts for situational constraints (e.g., price), while BIV adjusts for differences in both situational constraints and physical product features. Viewed in this manner, our approach allows the analyst to develop alternative measures of brand performance which account for the underlying determinants of market share.

Brand Intangible Value should be regarded as a diagnostic tool which provides information about the relative importance of non-product variables in building a strong brand (e.g., the cumulative impact of advertising, channel power etc.). In certain contexts, BIV may be a more important brand statistic than BV because BIV attempts to measure factors which are difficult for competitors to emulate. However, our operationalization of BIV must be interpreted cautiously. Because BIV is a residual measure of utility, its validity clearly depends upon the way in which Brand Value is defined in the choice model. Moreover, the BIV measure is based upon a particular set of physical features used to measure the tangible product. To obtain a managerially meaningful BIV scale, the researcher must take care to identify the most relevant physical features in the product category.

The difficulty of defining the tangible product is part of the larger question of the separability of the value of a brand from the value of the rest of the firm. Although our research assumes that separability exists, this issue is a subject of considerable debate [see Barwise et al. (1990)]. The practical impact of this debate for our approach is that different managers may agree about brand value (BV), but may disagree about the size of the intangible component (BIV). Nevertheless, BIV can be helpful by identifying brands which enjoy unexpectedly large (or small) market shares relative to competitors with similar physical features.

This research should be viewed as a first step in measuring brand equity using scanner data. Our empirical application is intended as an illustration of the approach, constrained by the specific data available. Further work is necessary to validate and replicate the results across product categories. This additional work would reveal whether simplified procedures based upon aggregate information could be used as approximations to our scanner-based measures of brand value. For example, it might be possible to develop empirical generalizations which allow the estimation of Brand Value using an index calculated from market share and average price.

A useful extension of our approach would be the development of scales which allow a comparison of products with the same brand name in different product categories. Such scales might provide new tools for studying the determinants of successful brand extensions. Given the increasing availability of retail scanning data, the approach presented here provides a framework for managers interested in behaviorally based measures of brand performance.

References


