Evaluation of Product-Country Image and Marketing Efforts Effects on Retailer-Perceived Brand Equity using PLS Path Modeling

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ABSTRACT

According to the literature product-country image (PCI) and marketing efforts are effective in brand equity. This paper studies the effects of the two variables on retailer-perceived brand equity and brand profitability performance. A questionnaire was prepared and distributed among 57 retailers of LG to be filled out. Based on the results, PCI and marketing efforts have significant effects on retailer-perceived brand equity. Also, retailer-perceived brand equity has a significant positive effect on brand profitability performance.

INTRODUCTION

Brand equity is the final desirability or the value added produced by a product through its brand such as Coca-Cola. Brand equity is a corporate asset which increases circulation of business cash (Simon & Sullivan, 1993). Researchers have shown that marketing decisions and market conditions affect brand equity (Yoo, Donthu and Lee, 2000). For example, Simon and Sullivan (1993) mentioned marketing expenses, sales force, marketing research expenses, brand age, share of advertisement, and method of entrance and product portfolio as the sources of brand equity. Other marketing activities such as use of public relations (Aaker, 1991), warranties, advertisement mottos, signs and packaging (Aaker, 1991), mental image of the company and the country producing the product and promotional events (Keller, 1993) and brand naming strategies (Heckler and Houston, 1998) have been also suggested as other sources of brand equity.

Intense concentration of marketing relations on brand equity is a part of vaster motivation for marketing responsiveness in general. The authorities agree that brands are very valuable and evaluation of them can yield a useful index for investment or purchase, especially for the beneficiaries (Egle and Kitchen, 2000). Knowing how marketing activities contribute in brand equity or damage it, marketing managers can develop better effective marketing programs. Managers need to promote those measures that construct brands and abstain from activities that may damage it (Yoo, Donthu and Lee, 2000).

Feldwick (1996) states that before 1990s brand image was a vague theory and first was used when advertisement surpasses other aspects in increasing sales and creating long-term loyalty. In most cases differences in evaluations and the prices paid to companies or brands can be an evaluation of the brand.

According to Keller (1996) the roles of integrative marketing relations on brand equity can be determined in two sections: first, establishment of brand in customer’s memory and creating powerful, desirable and even connotations with it; and second, the marketers can create motivation, capability and an opportunity for the customers for processing messages and retrieving data from their memories when they select a brand.

Brand equity has several advantages for its owners. Brand equity has a positive relationship with brand loyalty. In exact words, brand equity increases the probability of selection of the brand that in turn causes consumer’s loyalty to the brand (Pitta and Katasanis, 1995).

One of the benefits of high brand equity is the possibility of brand development to other product categories. Usually IBM development is defined as “use of the existing brand for entering into a new product category” (Aaker and Keller, 1990). When a brand is matched with new brands, development of the new brand will be less costly and will cause more sales (Smith and Park, 1992). Development of successful brands plays a significant role in increasing the equity of the principal brand (Dacin and Smith, 1994; Keller and Aaker, 1992) although unsuccessful development of brand can decrease the equity of the principal brand (Loken and John, 1993).
Aaker and Keller (1990) developed a model for consumer’s evaluation of brand development and some other authors have tried to generalize their model (Barrett et al., 1999; Bottomley and Doyle, 1996).

Brand equity increases consumers’ satisfaction for paying bonus prices, possibility of brand licensing, efficacy of marketing relations, shops’ satisfaction for participation and support, consumers’ elasticity for price decrease and lack of elasticity for price increase and decreases company’s risk of damage by marketing competitive activities and in crises (Barwise, 1993; Farquhar et al., 1991; Keller, 1993; Keller, 1998; Pitta and Katasani, 1995). Furthermore, brand equity plays a significant role in service-provider companies as robust brands can increase confidence in intangible products (Berry, 2000) and can empower customers to comprehend them better. Brands decrease purchase services safety, social and monetary risks that are impediments for evaluation of services before purchase. Also, higher levels of brand equity increase customer’s satisfaction, repurchase intention and fidelity (Kyung et al., 2007). Kohli et al. (2001) studied validity and brand equity, Pappu and Quester (2006) analyzed satisfaction and brand equity, Ross-Wooldridge et al. (2004) worked on brand equity and brand (Kyung et al., 2007).

Methodology:
Research methodology in this paper is of correlation type. In other words, the main objective of this research is studying the relationship between mixed marketing elements and retailer-perceived brand equity. Fig. 1 shows the conceptual model of this research.

![Conceptual Model of the Research](image_url)

**Source**: Baldauf, et al. (2009)
PRO: Promotion
SPI: Supplier- perceived image
PL: Price level
RPBE: Retailer-perceived brand equity
BPP: Brand profitability performance
PD: Price development
PCI: Product-country image

A questionnaire was used to study the relations of the variables. The questionnaires were submitted to 70 LG retailers and 57 analyzable questionnaires were obtained.

Data Analysis:
Structural equation modeling method was used to analyze the data and test the hypotheses. Structural equation modeling is a powerful multivariate technique of multivariate regression family; in exact words, it is a general linear model expansion using which the researcher can test a set of regression equations simultaneously. Structural equation modeling is a comprehensive statistical perspective for testing hypotheses about the relations among observed and hidden variables that has been named as covariance structural analysis, causative modeling and Lisrel, but, usually named as Structural Equation Modeling (SEM).

The following structural equations can be written for the model suggested in the previous section:

\[
RPBE = \beta_0 + \beta_1 SPI + \beta_2 PL + \beta_3 PD + \beta_4 PRO + \beta_5 PCI + \epsilon_1
\]

\[
BPP = \beta_{10} + \beta_{11} RPBE + \epsilon_{11}
\]
In this section, with respect to the model, presented in the previous section, the model has been estimated and its validity was examined using PLS Path Modeling Technique. First, after extracting the answers, manifest variables were normalized as follows: The original items $Y_i$, scaled from 1 to 5, are transformed into new normalized variables $X_i = \frac{100}{4} (Y_i' - 1)$. The minimum possible value of $X_i$ is 0 and its maximum possible value is equal to 100. If there are missing data for variable $X_i$, they are replaced by the mean of this variable.

After specifying the relationship between the variables of the model, using PLS Path Modeling Technique, all the coefficients and parameters were estimated. For this purpose, VPLS 1.04 software was used to estimate the relationship between the latent variables of the problem.

![Fig. 2: Estimated model using VPLS.](image)

We know that a PLS path model consists of a structural model and a measurement model. Then, the validation of a PLS path model requires the analysis and interpretation of both the structural and the measurement model. This validation can be considered as a two-stage process: the assessment of the measurement model, and the assessment of the structural model. (Henseler et al., 2009).

**Assessing the Structural Model:**
According to Chin’s theory, $R^2$, that is just measured for endogenous variables and shows the variance of endogenous latent variables, can be interpreted as noticeable, average and weak for values of 0.67, 0.67-0.33 and less that 0.19 respectively. Also, in a specific model including endogenous latent variables with only one or two exogenous latent variable(s), average amount of $R^2$ is acceptable (Trujillo, 2009). In this study, $R^2$ value is equal to 0.503, Therefore, $R^2$ value of the model is acceptable, (Trujillo, 2009).

Also, average Redundancy of the model was estimated to be 0.63. High redundancy means high ability to predict (Trujillo, 2009).

**Assessing Measurement Models:**
In this section, we must evaluate three aspects of reflective measures
- Unidimensionality of the indicators
- Check that indicators are well explained by its latent variable
- Assess the degree to which a given construct is different from other constructs

**Unidimensionality of the indicators:**
Some recent tools have been proposed to evaluate unidimensionality of PLS-PM reflective blocks (Sahmer et al., 2005), but the most common methods employed for this purpose are the following three indicators:
- Check the first eigenvalue of the MVs correlation matrix
- Calculate the Cronbach’s alpha
- Calculate the Dillon-Goldstein’s

In this paper, Unidimensionality of the indicators was measured using Cronbach's alpha coefficient. If the coefficient is more than 0.7 the reliability of the model is high and if the coefficient is smaller than 0.6, the model has low reliability (Henseler et al., 2009). Although Cronbach's alpha coefficient for PRO is less than 0.6, but the average of Cronbach's $\alpha$ coefficients of the model is more than 0.7, showing that the reliability of the model is confirmed in general.
Check that indicators are well explained by its latent variable:

In this case, we check it by means of three tools:

- **Communality:**
  Communality is calculated with the purpose to check that indicators in a block are well explained by its latent variable (Trujillo, 2009). In this research, the mean communality of the model, was estimated 0.6189, which is the average of all the block communalities.

- **Composite Reliability:**
  Composite Reliability is the criterion of the model reliability. For this criterion, a value less than 0.6 indicates a lack of reliability (Henseler et al., 2009). The value of this criterion in this study is more than 0.6, which shows the high reliability of the model.

- **AVE:**
  To calculate the convergent validity, Fornell and Larcker suggested AVE. AVE should be larger than 0.50 which means that 50% or more variance of the indicators should be accounted for (Henseler et al., 2009). The AVE of the model is much more than 0.5, so the convergent validity of the model is confirmed.

### Table 1: Reliability, Cronbach’s α and AVE

<table>
<thead>
<tr>
<th>Construct</th>
<th>Composite Reliability</th>
<th>AVE</th>
<th>Cronbach’s α</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCI</td>
<td>0.52</td>
<td>0.85</td>
<td>0.779</td>
</tr>
<tr>
<td>PL</td>
<td>0.79</td>
<td>0.87</td>
<td>0.824</td>
</tr>
<tr>
<td>PD</td>
<td>0.76</td>
<td>0.85</td>
<td>0.732</td>
</tr>
<tr>
<td>PRO</td>
<td>0.72</td>
<td>0.87</td>
<td>0.825</td>
</tr>
<tr>
<td>RPBE</td>
<td>0.68</td>
<td>0.58</td>
<td>0.831</td>
</tr>
<tr>
<td>BPP</td>
<td>0.64</td>
<td>0.84</td>
<td>0.776</td>
</tr>
<tr>
<td>SPI</td>
<td>0.78</td>
<td>0.89</td>
<td>0.81</td>
</tr>
<tr>
<td>AVERAGE</td>
<td>0.698</td>
<td>0.82</td>
<td>0.716714</td>
</tr>
</tbody>
</table>

Assess the degree to which a given construct is different from other constructs:

We evaluate the extent to which a given construct differentiates from the others. This is done by verifying that the shared variance between a construct and its indicators is larger than the shared variance with other constructs. In other words, no indicator should load higher on another construct than it does on the construct it intends to measure. We calculate the correlations between a construct and other indicator besides its own block. If an indicator loads higher with other constructs than the one it is intended to measure, we might consider its appropriateness because it is not clear which construct or constructs it is actually reflecting (Henseler et al., 2009).

On the other hand, regarding that the weight of the manifest variables of the model are all positive, all measurement indicators have explained their own latent variable correctly.

### Conclusion and Discussion:

According to the results of model hypotheses testing, the effects of SPI, PRO, PL, PCI on RPBE are significantly positive but the effect of PD, although is negative on RPBE, is not significant at level of 95%. Also, according to the results, SPI, PL and PCI have the highest effects on RPBE respectively. Also, based on the results, a significant positive relationship was found between RPBE and BPP.

### Table 2: Structural Model

<table>
<thead>
<tr>
<th></th>
<th>Entire Sample estimate</th>
<th>Mean of Subsamples</th>
<th>Standard error</th>
<th>T-Statistic</th>
<th>Findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCI-&gt;RPBE</td>
<td>0.2221</td>
<td>0.2358</td>
<td>0.1131</td>
<td>1.9644</td>
<td>Support</td>
</tr>
<tr>
<td>SPI-&gt;RPBE</td>
<td>0.3960</td>
<td>0.4042</td>
<td>0.1365</td>
<td>2.9013</td>
<td>Support</td>
</tr>
<tr>
<td>PD-&gt;RPBE</td>
<td>-0.1130</td>
<td>-0.1331</td>
<td>0.0841</td>
<td>-1.3444</td>
<td>Unsupported</td>
</tr>
<tr>
<td>PL-&gt;RPBE</td>
<td>0.3580</td>
<td>0.3087</td>
<td>0.1116</td>
<td>3.2090</td>
<td>Support</td>
</tr>
<tr>
<td>PRO-&gt;RPBE</td>
<td>0.2157</td>
<td>0.2152</td>
<td>0.1093</td>
<td>1.9733</td>
<td>Support</td>
</tr>
<tr>
<td>RPBE-&gt;BPP</td>
<td>0.4830</td>
<td>0.5541</td>
<td>0.0858</td>
<td>5.6314</td>
<td>Support</td>
</tr>
</tbody>
</table>

### REFERENCES


