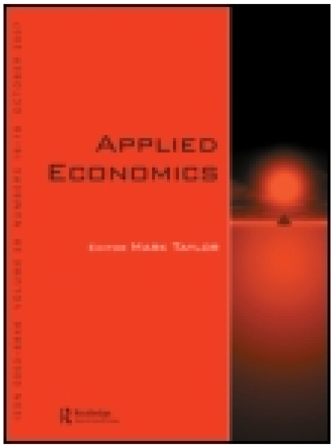

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Brand power index - using principal component analysis

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Brand power index – using principal component analysis

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A relatively simple approach is proposed to evaluate the strength of brands from the viewpoint of consumers. It employs Principal Component Analysis (PCA), in which the coefficients of the first principal component are used as the weight for developing our study's final 'product', the Brand Power Index (BPI). Empirical consumer-survey data of two product categories: televisions and mobile phones illustrate that the patterns of PCA results for both televisions and mobile phones are extremely similar. The biplots reveal that the leading brands in both product categories had positive component scores; more than a dozen following brands had positive first component scores and negative second component scores in both categories. This led us to a visual examination of the data on certain leading brands with regard to their brand excellence.

Keywords: biplot; brand power index; consumer survey; principal component analysis

JEL Classification: A11; M31

I. Introduction

'Brand strength' or 'Brand equity', both as a concept and as a metric, has been a subject of interest for scholars and marketing consultants alike. Various marketing consulting firms, such as Landor, Interbrand and Brand-Finance, use different approaches to demonstrate the strength or value of a brand, as well as to 'rank' brands for marketers' and investors' reference. Examples of empirical market power research and its relationship to price and brand refer to Vickner and Davies (1999) and Kong (2004) and references therein.

Although knowing the 'value' of a brand can have tremendous meaning for managers, the time and money consumed by the valuation process are, not surprisingly, significant. During the brand-ranking process, two of the critical components are the consumer survey and the converting calculation. The awareness, preference for, and/or uniqueness of a brand only exist in consumers' minds, and thus have to be retrieved through consumer surveys and then converted into some sort of comparable, discernable value. Therefore, the purposes of this study are to re-examine and identify the major dimensions of brand strength via a consumer survey and Principal Component Analysis (PCA), and to further propose a relatively simple index to illustrate the strength of brands in a product category. Hereafter, we call this index the 'Brand Power Index' (BPI).

Two closely related techniques, PCA and factor analysis, are used to reduce the dimensionality of multivariate data. In these techniques, the correlations and interactions among the variables are summarized in terms of a small number of underlying factors. These methods rapidly identify key variables or groups of variables that control the systems being studied. Generally, PCA seeks to represent p correlated random variables by means of a reduced set of uncorrelated variables, which are obtained by transforming the original set into an appropriate subspace. The uncorrelated variables are chosen to provide a good linear combination of the original variables, in terms of explaining maximal variance and orthogonal directions in the data. The resulting dimension reduction also permits a graphical representation of the data so that significant relationships among observations or samples can be identified.

The application of PCA to the problem of developing an index and ranking system is evident in many different fields, including economics, education, the environment, finance and sports (see Dawkins, 1989; Naik and Khattree, 1996;

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Steiner, 2006; Shih *et al.*, 2007). At the same time, Data Envelopment Analysis (DEA) has also been applied to the problem of ranking alternatives and assessing the performance of organizations with multiple homogenous decision units that produce several outputs as the result of a variety of inputs (see Boyd and McClelland, 1999; Boyd and Pang, 2000). Zhu (1998) and Premachandra (2001) described the joint use of PCA and DEA in ranking the decision-making units in such situations. However, the two papers came to different conclusions as a result of applying DEA and PCA approaches to developing rankings under certain circumstances. Kardiyen and Örkcu (2006) showed consistent results when they applied both DEA and PCA approaches to the economic performance of EU member countries based on the simulated data set. In this article, we have chosen to focus on the PCA approach. Other discussions related to ranking and sorting data may be found in Nishisato (1994).

In this article, we apply PCA to obtain the BPI for evaluating the strength of brands from the viewpoint of consumers. The method is illustrated through the use of two product categories in Taiwan. The empirical studies show that the first principal component provides the weights for computing the resulting BPI as well as explains a relatively high proportion (near 90%) of variation of the data. The first two Principal Component (PC) scores together present the difference among brands. In addition, the proposed approach is easily implemented for practitioners since PCA is one of the basic tools for multivariate data analysis.

II. Dimensions of Brand and Power Index

Although the definition and dimensions of brand equity are often debated (Biel, 1992), most measurements of brand strength or brand equity contain two major components: brand awareness and brand preference (Owen, 1993). Owen (1993) suggests that in order to be powerful, a brand has to be not only well-known but also highly regarded by consumers. On the other hand, brand awareness and brand image are also considered sources of brand equity (Keller, 1993). 'Brand awareness' is generally the element recognized as essential by most scholars. Two facets, that of (unaided) brand recall and (aided) brand recognition, are usually measured as representations of brand awareness (Keller, 1993; Cobb-Walgren *et al.*, 1995). Furthermore, within the brand image, Keller (1998) emphasized three facets: the strength of brand association, the favourability of brand association, and the uniqueness of brand association. A brand may evoke many kinds of associations in consumers, but only a positive brand image can lead to brand preference (Cobb-Walgren *et al.*, 1995), high brand regard (Owen, 1993), and/or positive brand meaning (Berry, 2000).

In further examining the concept of brand image, the fit between brand image and product category may become problematic if the purpose of the BPI is to evaluate brands across product categories. For example, 'lovely' might be an excellent brand image for designer clothing, but not so good for sportswear. The uniqueness of brand association (Keller, 1998) is not considered in this study, then, because the ideal BPI is applicable across all product categories.

Other than brand preference, this study would like to extract another indicator of brand image valuable across product categories. Blackston (1992) indicated the importance of 'trust' in a brand, as well as customer satisfaction with the brand. A brand might stand for loveliness or ruggedness, but it must be worthy of trust. Trustworthiness is also one of the dimensions of brand equity suggested by Lassar *et al.* (1995). Trustworthiness, called 'brand confidence' here, is thus another dimension of BPI in this study.

Without the behavioural dimension, BPI would not be complete. The most common behavioural dimensions for measuring brand equity are purchase intention, purchase, usage and brand loyalty (Aaker, 1991). A prestigious brand which every consumer reveres – but very few actually buy – is not perceived as having high brand equity or exhibiting leadership.

In sum, the dimensions considered in this study include the awareness, preference, confidence, purchase behaviour, and loyalty or longing toward a brand. All these dimensions are applicable to various product categories, allowing us to create a BPI which is applicable across product categories. PCA is also employed to detect the importance (i.e. weight) of these dimensions in composing the index.

III. Application of PCA on BPI

PCA is a statistical method that explains the correlation structure explained by the correlated number of p variables with the uncorrelated number of k variables which the linear combinations of the original variables provide ($p > k$). Eigenvalues and eigenvectors of the covariance or correlation matrices are used to find the linear combinations of the p variables in the data matrix, X. Let $\sum$ be the covariance matrix and ρ the correlation matrix of the random vector, $[x_1\ x_2 \ldots x_p]$, whereby $\lambda_1 \geq \lambda_2 \geq \geq \lambda_p$ denotes the eigenvalues, and $l_1, l_2, \ldots, l_p$ are the corresponding orthogonal eigenvectors of the correlation matrix. Linear combinations of the variables can be calculated by $PC_i = l_i' X\ (i = 1, 2, \ldots, p)$. The explanation ratio of the total variance of the kth PC is described as $\frac{\lambda_k}{\lambda_1 + \cdots + \lambda_p}$. Units are then ranked according to values of scores.

The aim of PCA is to find out new independent measures that represent different linear combinations. One of the primary benefits of using PCA is that the directions of greatest variability give the most information about the configuration of the data in multidimensional space. The first PC has the greatest variance and extracts the largest amount of information from the data. The second component is orthogonal to the first one and has the greatest variance, in that the subspace is orthogonal to the first component; and, it extracts the greatest information in that subspace, and so on.

The PCs also minimize the sum of the squared deviations of the residuals from the projection into linear subspaces of dimensions 1, 2, etc. The first PC gives a line such that the projections of the data onto this line have the smallest sum of squared deviations among all possible lines. The first two PCs define a plane that minimizes the sum of the squared deviations of the residuals, and so on.

It should be noted that both covariance and correlation matrices can be used to conduct PCA. However, the two may not be suited for the same applications, and may also lead to different conclusions (see Naik and Khattree, 1996).

IV. Sampling and Survey Process

This survey was conducted in the three largest cites of Taiwan: Taipei, Taichung and Kaohsiung, located in the north, middle and south of Taiwan, respectively in spring 2006. Two product categories, televisions and mobile phones, and 40 brands (of both televisions and mobile phones) were included in our survey. The top 10 TV brands covered 86.80% of the market; market share was less than 0.1% after the 30th brand. Similar to the TV industry, the first 10 mobile phone brands took up 84.97% of the market, and market share was less than 0.1% after the 31st brand (see Easter Integrated Consumer Profile Database (EICPD), 2006). The survey listed top 40 brands which almost covered all available brands in each category (that is, televisions and mobile phones).

Because only 5.2% of consumers under the age of 25 have any influence on the decision to purchase a TV set for family in Taiwan (EICPD, 2006), we decided that only consumers aged 25 and up were qualified to participate in the television portion of our survey. In contrast, a mobile phone is a personal product, and 82% of 15 to 19-year-olds in Taiwan own a mobile phone (EICPD, 2006). Therefore, our sample frame of mobile phone consumers started at age 15, in this study. The proportion of our sample in each city is decided based on population as well as on age and gender quotas. Through a convenient sampling process, 1540 consumers for each product category were interviewed.

Respondents answered 11 questions for each category, which included the five dimensions of the BPI: brand awareness, brand preference, brand confidence, brand selection and brand longing. All the items are listed here; italics denote the variable names in the following analyses.

A. Brand awareness:
- Q1. No Aided Recall (multiple brands): *recall*
- Q2. Aided Recognition (multiple brands): *recog*

B. Brand preference:
- Q3. Three Preferred Brands: *prefer*
- Q4. Most Preferred Brand: *mostprefer*

C. Brand confidence:
- Q5. Three Trusted Brands: *trust*
- Q6. Most Trusted Brand: *mosttrust*

D. Brand selection:
- Q7. Used Brand (multiple brands): *used*
- Q8. Currently Owned Brand (multiple brands): *owned*
- Q9. Most Frequently Used Brand: *mostused*
- Q10. Most Recently Purchased Brand: *purchased*

E. Brand longing
- Q11. Brand most likely to be chosen in the Next Purchase: *next*

Results of BPI

The proportions of every brand selected for each question were obtained first. According to the boxplot and histogram, the distributions of each variable for both televisions and mobile phones are quite similar and all appear to be skewed to the right. The right skewness is obviously due to outlying leading brands. Four outlying brands appear in all the variables, except *recog,* for TV data. While four or six outliers are revealed in the different variables of mobile phone data, this indicates a larger variation in the mobile phone data than in the TV data. Thus, brand differences in the mobile phone category appear to be more distinct than those in the television category. Although no outlier exists, the variable *recog* has the largest range among 11 variables.

We then examined the correlation matrix of these 11 variables. Highly correlated relationships are present among these variables, except for the variable *recog*. The values of correlation coefficients vary between 0.63 and 0.99 for mobile phone data, and 0.60 to 0.99 for television data. The correlation coefficients of any two variables are again quite similar in both product categories. Despite the differences in markets, industries and even interviewees, the data structures for these two categories are quite similar to one another. Moreover, the variable *recog* is the distinctive one from the other variables according to its own distribution as well as the relationships with other variables.

The PCA is then applied to these two data sets. The first PC explains 87.1% and 89.1% of the variation in the television and mobile phone data, respectively, while more than 98% of the variation is explained by the inclusion of the second PC. If the variance–covariance and correlation matrices have all nonnegative entries, all coefficients of the first principal component will have the same sign according to the Perron-Frobenius theorem (see Naik and Khattree, 1996). The first component score is therefore used to establish the BPIs as well as the ranking for the television and mobile phone categories (Table 1). The values of the BPI are obtained by first standardizing the scores, then transferring those scores to the values of the corresponding cumulative probability based on the standard normal distribution, and finally multiplying the probability by 100.

It should be noted that we used the covariance matrix to conduct this PCA, rather than using the correlation matrix. Naik and Khattree (1996) argue that the use of a correlation matrix may destroy the natural variability in the data for certain variables. In addition, we have not taken the approach of Kardiyen and Örkcu (2006) in choosing weights for the scores in this study. Rather, the first component score is used solely for evaluating the brand power. When two or more PC scores are used, further considerations about the choice of weights for computing BPI may be warranted. Nevertheless, we expect positive values for all pairwise correlation coefficients among the original variables as the empirical studies by Naik and Khattree (1996). On the other hand, the first PC would provide with a relatively high proportion on explained variation of the original data.

Standardization is called for because of the rightward-skewed distribution of the scores in both categories (Fig. 1). The solid and dashed lines are the estimated density curves of the first PC scores for the television and mobile phone data, respectively. The estimated density of the scores for the mobile phone category looks slightly more skewed than that of the television category. Furthermore, the two leading brands in the mobile phone category are more distinct. Notably, the ranking

Table 1. BPI and ranking

		TV					Mobile phone		
Rank	NO	Brand	Score	BPI	Rank	NO	Brand	Score	BPI
1	1	SONY	1.28	99.97	1	1	NOKIA	1.61	100.00
2	2	Panasonic	1.12	99.85	2	2	MOTOROLA	1.28	99.94
3	3	SAMPO	0.58	93.89	3	3	Sony Ericsson	0.58	92.81
4	4	TATUNG	0.52	91.66	4	4	Panasonic	0.42	85.46
5	7	TOSHIBA	0.42	86.63	5	5	BENQ	0.37	82.39
6	5	kolin	0.33	81.09	6	6	SAMSUNG	0.26	74.71
7	8	TECO	0.31	79.53	7	7	OKWAP	0.16	65.65
8	6	SANYO	0.28	76.91	8	8	PHS	0.09	59.14
9	9	HITACHI	0.24	74.22	9	10	SIEMENS	0.09	59.01
10	11	LG	0.19	69.25	10	9	ASUS	0.07	56.59
11	10	PHILPS	0.13	63.96	11	11	ALCATEL	0.04	53.90
12	12	PROTON	0.12	62.49	12	12	PHILIPS	0.03	53.22
13	13	SHARP	0.10	60.00	13	14	LG	0.01	51.07
14	14	SAMSUNG	−0.02	48.04	14	13	SHARP	−0.03	47.02
15	16	Pioneer	−0.03	46.78	15	15	SAGEM	−0.04	45.63
16	15	MITSUBISH	−0.04	45.33	16	16	NEC	−0.06	43.77
17	17	JVC	−0.06	43.88	17	17	DBTEL	−0.08	42.29
18	20	BENQ	−0.10	39.46	18	18	SANYO	−0.11	39.23
19	19	Westinghouse	−0.11	38.10	19	19	Dopod	−0.14	35.78
20	18	TERA	−0.12	37.34	20	20	Innostream	−0.15	35.45
21	21	SYNCO	−0.13	36.19	21	23	TOSHIBA	−0.16	34.54
22	22	AOC	−0.16	33.94	22	21	GPLUS	−0.16	34.26
23	24	polyview	−0.18	31.47	23	24	MITSUBISHI	−0.16	34.24
24	23	CHUN	−0.19	31.03	24	25	SAMPO	−0.16	34.00
25	26	ViewSonic	−0.19	30.87	25	22	APBW	−0.17	33.75
26	25	RCA	−0.20	29.51	26	26	HITACHI	−0.17	33.62
27	27	SOWA	−0.21	28.68	27	27	ARCIOA	−0.20	30.83
28	28	FUJITSU	−0.24	26.08	28	30	TATUNG	−0.22	29.29
29	29	Gibson	−0.26	24.79	29	29	Snio	−0.22	29.20
30	30	TFC	−0.28	23.10	30	28	PANTECH	−0.22	28.90
31	31	CH	−0.29	22.28	31	31	PierreCardin	−0.22	28.64
32	33	MAG	−0.29	21.80	32	33	JOWIN	−0.24	27.29
33	32	Digimaster	−0.29	21.70	33	32	Toplux	−0.24	26.95
34	34	JEAN	−0.30	21.16	34	35	GIGABYTE	−0.25	26.61
35	35	VITO	−0.31	20.65	35	36	XG	−0.25	26.16
36	36	Powersonic	−0.32	20.07	36	34	ELIYA	−0.26	25.64
37	37	Colortac	−0.32	19.92	37	37	JMAS	−0.27	24.46
38	38	Esonic	−0.32	19.47	38	38	BIRD	−0.28	24.12
39	40	MARTEK	−0.33	19.22	39	40	xcute	−0.28	23.76
40	39	VTEK	−0.33	19.15	40	39	VKMobile	−0.28	23.72

does not change whether the standardization is carried out or not.

Because of the monotone relationship between the score and BPI, both can be used for ranking. However, using BPI has some advantages. First, it gives the relative position of each brand within its own category. Second, the value of BPI falls between 0 and 100, which can be interpreted as '*the value of brand power*'. Finally, using BPI allows for meaningful comparison in different years and even for different goods.

It should be pointed out that the original ordering (named as NO in the tables) of each brand descends in relation to the first variable, *recall,* which indicates the percentage of unaided brand awareness. The ranking of our BPI is quite similar to the ranking according to *recall,* especially for mobile phone data.

The first component can be interpreted as a measure of size, or a degree of expression of a certain feature; while the second, third, (and so on) components be interpreted as having some structure of that feature. Dawkins (1989) and Naik and Khattree (1996) conducted a similar analysis on the national track records using Olympic track record data. The first two components, as given, were of considerable interest. Table 2 presents the coefficients (or weights) of various brand measures for computing the first two component scores. All the signs of the coefficients for the first PC appear positive in both the television and mobile phone data. We therefore used it as a basis for the development of our rankings, which are shown in Table 1.

The first PC represents a weighted average of all measures of brand power. *Recog* has the greatest weight in the indicator of the brand power of both televisions (0.66) and mobile phones (0.53). This comes as little surprise, as consumers must recognize a brand before they can decide to like, trust, or choose it. *Recall* is the next most important contributor, followed by *prefer* and *trust,* which both bear similar weights. The weights of *prefer* and *trust* are close to the weight of *recall.* Obviously, consumers can easily recall the brands that they

Table 2. Coefficients in the first two principal components for both TV and mobile phone data

	TV		Mobile phone	
	First PC	Second PC	First PC	Second PC
recall	0.380	0.088	0.434	0.069
recog	0.657	−0.707	0.526	−0.821
prefer	0.338	0.358	0.378	0.273
mostprefer	0.148	0.244	0.164	0.192
trust	0.338	0.377	0.377	0.285
mosttrust	0.152	0.257	0.170	0.213
used	0.289	0.132	0.350	0.179
owned	0.154	0.118	0.151	0.110
mostused	0.121	0.108	0.131	0.109
purchased	0.116	0.096	0.126	0.101
next	0.125	0.212	0.126	0.131

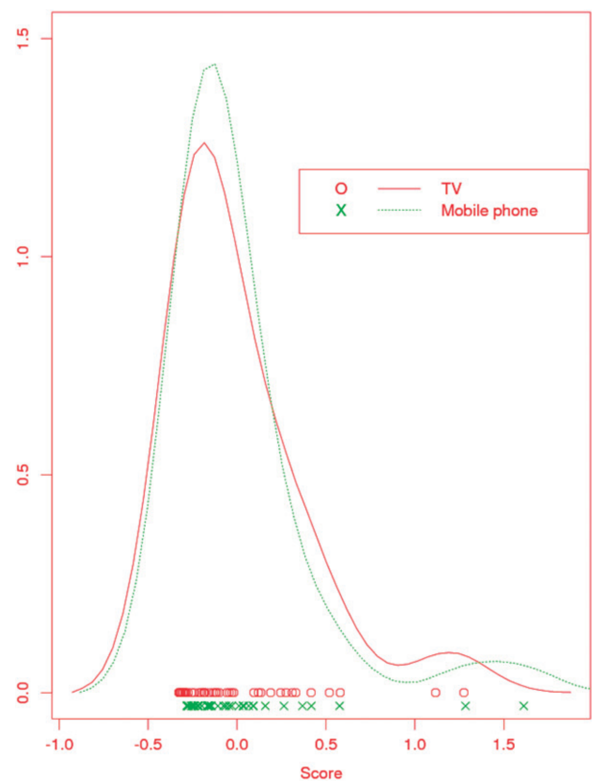

Fig. 1. The estimated probability density plots of the first PC scores for TV and Mobile phone data

prefer and trust. The similar weights of *prefer* and *trust* may also imply that consumers' attitudes of preference and reliance are hardly distinguishable. That is, they prefer what they trust and trust what they prefer. The rest of the variables are all related to the concept of 'final selection' which includes the most preferred brand, the most trusted brand, the most purchased brand, and so on. The higher score on the first PC correspond to better performance of a brand.

The only negative coefficient in the second PC is associated with *recog*; while the others are all positive. The fact that

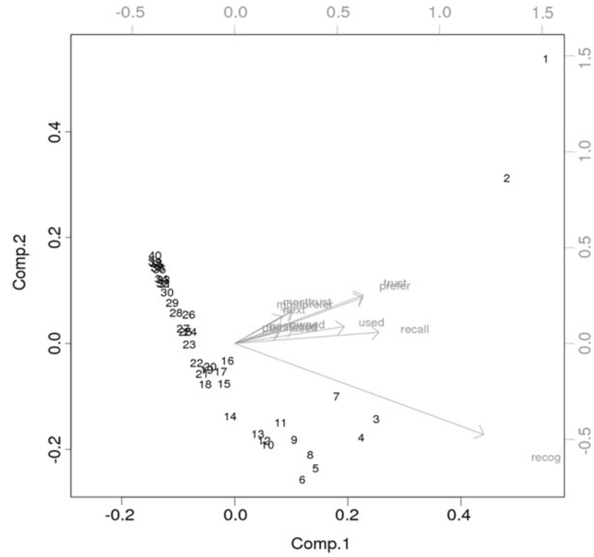

Fig. 2. The biplot for TV data
Note: The numbers on the figure refer to brands listed in Table 1.

recog's sign is opposite from the others' indicates that consumers can recognize brands that they neither like nor care about. The score of the second component can be interpreted by the concept of an inert or inept set of brands (Kakkar, 1976). An 'inert' brand is one that consumers recognize after being reminded, but feel indifferently towards. Inept brands are those that consumers can recognize, but toward which they hold negative attitudes. These two forms of brand recognition account for the negative coefficient associated with *recog* in the second PC.

The order of the first PC scores here is not changed as using the weights to the original data as shown in Bradlow (2002), neither the pattern of the first two PC scores as the biplot in the consequent subsection. In this study, we executed all computations and graphics by using the statistical computing package S-PLUS.

Biplots

The biplot of Gabriel (1971) is an exploratory graphical tool which can illustrate the correlation structure among variables, the similarity of observations, and the relative values of data points for the variables measured. Figures 2 and 3 present the biplot of the first two PC scores for television and mobile phone data, respectively. These two figures demonstrate a similar pattern in the length and direction of variables as well as in the data points. The length of the variable vector in a biplot, relative to its length in the original *n*-space, indicates how well the two-dimensional biplot represents that vector.

The angle between the two variable vectors reflects their pairwise correlation, as is evident in this two-dimensional projection. Apart from the variable *recog,* the other 10 variables point to the same direction. The correlation is the cosine of the angle. Hence, a 90° angle indicates zero correlation; a 0° or 180° indicates correlation of 1.0 or −1.0, respectively. Most of the pairwise correlations among these variables in both datasets are close to 1, except in the case of the variable *recog*. This coincides with the relatively high

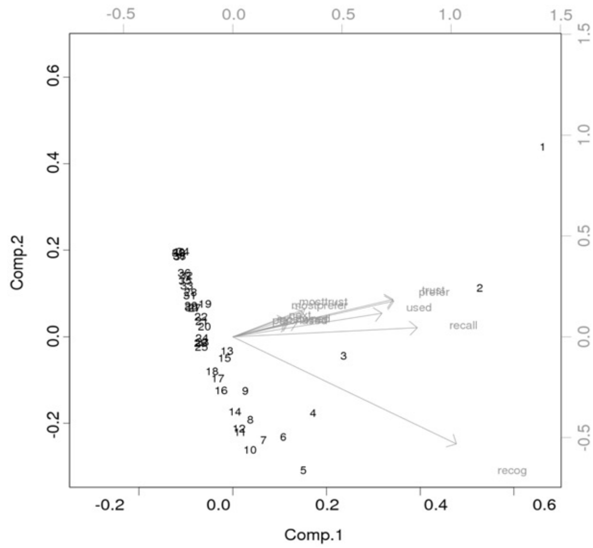

Fig. 3. The biplot for mobile phone data
Note: The numbers on the figure refer to brands listed in Table 1.

values of the correlation coefficient that we obtained previously.

The PCA-determined rankings are essentially the ordinary means of the suitably normalized data, which reflect the specialized nature of the geometry of the data set (see Dawkins, 1989). The spatial proximity of individual observations reflects their similarities with respect to this particular set of variables, as seen in the two dimensions. The first two leading brands, located at the upper-right quadrant in both plots, appear quite far away from the bulk of the other points. As discussed with regard to Fig. 1, the first PC scores in the mobile phone data are more skewed than those in the television category; here, the first two brands in the television category are more distinct in Fig. 2. The third brands in both the television and mobile phone categories have the same score value, 0.58, but the scores of the first two leading brands for televisions are 1.12 and 1.28, whereas they are 1.28 and 1.61 for the mobile phone categories. The scatter pattern of those brands with negative values in the first PC score is quite similar in both Figs 2 and 3, which are located at the left part of the biplot. It is particularly interesting to see the difference in the location of the data points in the lower-right quadrants for both plots, which means these brands have positive values in the first PC scores, but have negative values in the second PC scores. The scatter patterns in Figs 2 and 3 may reflect the essentially different markets of these two categories. However, those brands that fall far behind the leaders show no difference in both categories.

Both leading brands show positive values along the two dimensions. If the first two components are used to calculate the values of BPI for all the brands in this category, the first two brands keep the leading position. However, the two first brands are actually outliers which have an influence on the estimates having to do with PCA (Chatterjee *et al.*, 1991). Outliers appear to be meaningful, here, as well as important from a practical standpoint. The leading brand, as the outlier, implies that there are absolute leaders in consumers' minds. However, outlying brands, as they exist in the data, may generate different scores when they are included in or excluded from the analysis. This might create problems when it comes to determining the relative positions of the other (nonleading) brands. To deal with the outlier situation, a robust estimation for PCA has been discussed in Engelen *et al.* (2005). Applying a robust PCA to these two datasets will lead to different PC scores (which are not the focus of this study), but the ranking remains almost the same as the original one.

V. Conclusions

In this article, we proposed a relatively simple method for evaluating the strength of television and mobile phone brands, from the viewpoint of consumers. The proposed method employs the principal component approach to obtain PC scores, and then transfers these scores to the values of cumulative probability. The coefficients of the first component are used as weights in the development of our final product, the BPI, which illustrates the strength of brands within a product category.

The results of the two major components for both product categories imply that brand strength surveys can be simplified in light of budget constraints. Brand recognition is the most crucial concept – and one which absolutely cannot be ignored when it comes to measuring brand strength. Recall, preference, and trustworthiness contribute similarly to the BPI. Surprisingly, the behavioural dimensions measured by *purchase* and *repeated purchase* are not critical, according to the results of this study. It is assumed that the pricing within a product category allows consumers to select their ideal brands, then consumers' behaviour patterns will be consistent with their preferences.

Our index can also be used for comparing different years and even different products because the questions are simple and can be consistent across product categories. Krzanowski (1979) propose an approach to the comparison of principal components between groups. Bradlow (2002) applies PCA to explore key features for longitudinal data, which may provide an alternative in regards to this issue. However, a complex sampling design is required when it comes to comparing changes in BPI over the course of several years. This is also one of ongoing researches of the authors.

The marketing implications of the PCA are illustrated in the biplot figures. The upper-right quadrant, with the two positive components, carries only two brands in both the telephone and mobile phone categories. Sony, Panasonic, Nokia and Motorola are the leaders in the television and mobile phone markets, respectively. Indeed, their leadership positions place them far ahead of the other brands. The bottom-right quadrant reveals a positive first component score and a negative second component score. More than 10 brands are located in this quadrant. Their BPIs are not low; that is, consumers can recognize them after being reminded, but bear no special feeling toward them. The bottom two quadrants content inert and inept sets of brands, although the cutting line may not locate right at the zero of the first component. The brands in the bottom-left quadrant have two negative components. These are brands that consumers hardly recognize, and toward which they have little feeling. The upper-left quadrant of the biplot matrix represents brands with a negative first component score and a positive second component score. The negative first component means that these brands are hardly known by consumers. Interestingly, however, the positive second component indicates that the few consumers who know the brand are loyal to it. The brands in this quadrant are typical niche market players. The biplot matrix may provide a better measure and operational definition of evoked, inert and inept sets of brands which has been argued by Narayana and Markin (1975, 1976) and Kakkar (1976), as well as identify the niche brands easily.

In this study, the patterns of PCA results for both television and mobile phone brands are extremely similar. The similar parts include: two components, recognition out leading all other variables, a negative recognition coefficient in the second component, and one or two leading brands as the outliers in the BPI. It is very likely that the PCA patterns evident in the BPI will be similar while a product category reaches the maturity stage of the product life cycle. Based on the notion of the 'law of mind' put forth by Ries and Trout (1993), only a few brands per product category can have a spot in consumers' minds. Most product categories are composed of few outstanding leading brands (as outliers) and a large set of inert and inept brands. This commonly seen composition of brands is very similar to the result of a principal component analysis found in this study.

As stated previously, the main purpose of BPI is to propose a relatively simple method to illustrate the brand strength, but without the intention to replace the monetary meaning of brand equity by Interbrand, and Brand-Finance. BPI is the first step to understand the brand strength in a market, but not as fruitful as some consulting tools, for example, Brand Asset Valuator (BAV) by Young & Rubicam (refer to the website http://www.yrbav.com/). BAV can point out the direction to a brand, such as knowledge, relevance, esteem and differentiation. However, BAV's survey questions would be relatively hard to design due to its consulting purpose, and then uneasy to make cross-category comparison. The beauty of BPI is the easy administration to all marketers and brand managers.

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