The Development of Dynamic Brand Equity Chase Model and Its Application to Digital Industry Based on Scanner Data

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Abstract

The purpose of this research is to develop a comprehensive modeling for measuring dynamics of brand power. We define brand power as brand specific coefficients to yield the sales volume for each period. The modeling consists of multinomial log it model for each product category, the brand-specific coefficients, mixture modeling and fuzzy clustering algorithm. We apply our modeling to TV scanner data in Tianjin China. The results show 5 brands have 12 to 23 times change on their brand power in a year. The lasting time of brand power spreads from 1 week to 12 weeks.

Keywords: *Scanner Data, Brand Equity, China, Appliance*

1. Introduction

The research about brand equity is not a new subject. The subject for primary brand equity is mainly divided into three; study for definition of brand asset (Sung and Bong Woo, 2000; Jung 1999), study for constitution (Chung and Bak, 2007;Choi and Rhee, 2004), study for effect (Kim, 1996; Kim, 2008), and so on. If we analyze the previous studies for brand equity measurement, we regard it as the measurement from the view of stock concept. In other words, they are only divided into a big or low brand without specific period mentioned. As a result, we are likely to find out in a newspaper that that Coca-coloa has the biggest brand equity and Samsung has the biggest among Korean companies.

Have brand equity and brand power been changed when time goes by? If changed, what should a marketer do? If a marketer knows the period that brand power is more vulnerable and instead price sensitivity is high, price cut as a marketing tactic is likely to be employed instead of advertising. On the other hand, if there is a period that brand power is strong and price sensitivity is low, price cut is unnecessary. Accordingly, if a marketer can specifically measure a certain term that brand power is high or low, it can a guideline for him/her to practically implement effective marketing budgets.

This study is to gauge brand equity as flow concept rather than stock concept that previous researchers have carried out, that is, we would like to show dynamic forms with evidence that brand equity has been fluctuated during a certain period. As a consequence, this makes academic contribution by presenting concrete evidence that brand power has been dynamically changed. Besides, at practical fields marketing activities can be adjusted by capturing brand power is high or small during the period.

2. Modeling

This study takes following steps to measure lasting time of brand power. Firstly, related variables influencing on sales volume are extracted by using multinomial logit model. In this process it is proven that besides brand, other marketing variables influence revenue. Accordingly, the extent which brand influences revenue separate from other marketing variables is measured by calculating brand-specific coefficients which becomes brand power influencing revenue during a certain period. Additionally, this modeling reflects competitive condition by simultaneously considering both brand and price of competitors.

The second step is to adapt mixture regression modeling to measure brand power extracted from multinomial logit model time to time. In case of adapting the equation of multinomial logit model into mixture regression model, some sub-equations can be measured and it is expected the highest and lowest brand equities are extracted during a research period.

The third step is to calculate post hoc probability to classify dynamic changes in brand-specific coefficients of the second step. Through that brand equity is classified high and low according to seasons, at which time researchers utilize fuzzy clustering algorithm.

2.1 step 1: multinomial logit model

The multinomial logit model has been used primarily to examine customer choice behavior, although it has also been used to examine various market phenomena such as market share forecasting, store selection behavior, price cut effect on a market, market segmentation, choice set change, and brand switching (Bucklin, Gupta, & Han, 1995; Buckiln & Lattin, 1991; Hardie, Johnson, & Fader, 1993; Gupta, 1988). The majority of these studies have utilized non-durables based upon scanner data.

If individual *i* confronted with a choice from a set, Ci, of alternatives, utility can be expressed as follows, where alternative k is one of the alternatives Ci;

$$U_{ik} = V_{ik} + \varepsilon_{ik} \qquad (1)$$
$$V_{ik} = u_{ik} + \beta X_{ik} \qquad (2)$$

where V_{ik} = a deterministic component of i's utility
ε_{ik} = a random component of i's utility
u_{ik} = an intercept for brand k
= brand specific coeffient for brand k
β = a vector of coefficients for variables X.

Both marketing variables and evaluative criteria are included in the X_{ik} vector. The ε_k are independently distributed random variables with a double exponential (Gumbel type II extreme value) distribution.

$$P(\varepsilon_k, \le \varepsilon) = \exp[-\exp(-\varepsilon)]$$
$$-\infty < \varepsilon < \infty \qquad (3)$$

We assume that individual *i* chooses the one with the highest utility among the alternatives.

$$p_{ik} = P\{ U_{ik} \geq U_{ij}, j \in Ci\} \quad (4)$$

Given assumptions (1)-(4), the conditional probability of choosing brand j can be expressed by the multinomial logit model (k=1, 2,..., m) as follows;

$$p_{ik} = \exp(V_{ik}) / \sum_{k=1}^{m} \exp(V_{im}) \quad (5)$$

where P_{ik} = the probability of choosing brand k.

This expression is known as the multinomial logit (Ben-Akiva & Lerman, 1993; Guadagni & Little, 1983).

Where, u_{ik} is an intercept for brand k or brand-specific coefficient for brand k. This is a brand power for brand k for a given time horizon as a stock approach.

2.2. Step 2: mixture regression model

On Chusok (Korean Thanksgiving Day) and the Lunar New Year's Day, customers feel different about brands or promotion. So if we construct multinomial logit model that is based on the sales database of the year and make just one price response function or sales promotion response function on the basis of it, we are likely to neglect the different aspects of dull and active seasons, promotion and non-promotion seasons, normal and abnormal seasons, and high-demand and low demand seasons. Furthermore, we are likely to neglect the different brand power for a given time horizon.

To reflect differences in customers' responses to brand, price and promotion in these different seasons, we applied mixture modeling to the multinomial logit model. This process will generate the several brand-specific coefficients.

Mixture model is to unmix the sample, to identify the segments, and to estimate the parameters of the density function underlying the observed data within each segment. Therefore in the first stage of multinomial logit modeling, we find the most appropriate brand-specific coefficient for brand k for whole time horizon. Then in the second stage, we apply the mixture model within the multinomial logit model and divide it into several brand specific coefficients that explain differences by time to time. Therefore the brand specific coefficient of the first stage can be seen as an aggregated brand specific coefficient, and that of the second stage, as a disaggregated brand specific coefficient.

2.3. Step 3: Post hoc Probability

Some brand-specific coefficients separate from the second step just shows that brand equity the highest, lowest, or middle. Therefore, we adapt fuzzy clustering algorithm to capture seasons at which brand brand is the highest, lowest and middle. Then, we are capable of matching which brand specific coefficients of the second stage are related to a given time period.

3. Application to Digital Industry

3.1 Sample: scanner data

The weekly scanner data for 32-inch TVs from one of major retailers in China is used with the period from Jan. 2008 to Dec. 2008 in Tianjin, China. Major five brands' price and sales volume data has been used.

3.2 Our model

The multinomial logit model will be employed to estimate beta coefficients for the model with dependent variables equal to weekly sales volume and independent variables of brand name and price.

$$V_{ik} = u_{ik} + {}_{pik}price_k \qquad (5)$$

where V_{ik} = utility assigned to brand k by consumer i
u_{ik} = the intrinsic utility/value of brand k for consumer i (brand-specific intercept)
$price_k$ = the net available price of brand k for consumer i
${}_{pik}$ = the parameters to be estimated for consumer i

4. Findings and Future Study

In the first place, the results of multinomial logit model for whole observations of this study are shown as Table 1. For the study Brand 1 appears the highest brand power, and then Brand 3. Brand 5 has the lowest brand power.

Secondly, the results applied a mixture model are showed at Table 1 under condition that entire observations are kept on the form of multinomial logit model. Brand 3 in segment 1 has the highest brand power, Brand 1 in segment 2 has the highest, and again, Brand 3 in segment 3 shows the highest. We define brand power as brand specific coefficients to yield the sales volume for each period.

Table 1. Aggregate and disaggregate brand-specific coefficients

	The first Stage	The second stage		
		Segment 1	Segment 2	Segment3
Intercept	332.8	72.6	205.2	1702.0
Brand 1	39.8	7.2	26.3	132.9
Brand 2	11.3	4.6	-4.6	89.4
Brand 3	34.9	11.9	17.8	276.8
Brand 4	-27.1	-3.1	8.5	-221.5
Brand 5	-58.8	-20.7	-48.1	-277.5
Price	-226.5	-32.8	-106.2	-1237.4
R^2	0.11	0.43	0.42	0.55
		0.88		

According to segments it is founded out that brand power is a different order. In segment 1 brand power is brand 3, brand 1, brand 2, brand 4, brand 5 in order, while in segment 2 brand powers is brand 1, brand 3, brand 4, brand 2, brand 5 in order. Segment 3 has the same order of brand power as segment 1, however the extent of that is different.

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Table 2. Post hoc probabilities for Brand 1 for each week

week	Segment 1	Segment 2	Segment 3	Classification to segment
2008. 01	0.0%	0.0%	100.0%	3
2008. 02	0.0%	99.9%	0.1%	2
2008. 03	0.0%	99.4%	0.6%	2
2008. 04	0.0%	0.0%	100.0%	3
2008. 05	0.0%	0.1%	99.9%	1
2008. 06	0.0%	99.5%	0.5%	2
2008. 07	0.0%	98.6%	1.4%	2
2008. 08	0.0%	99.8%	0.2%	2
2008. 09	0.0%	99.7%	0.3%	2
2008. 10	0.0%	99.9%	0.1%	2
2008. 11	0.0%	99.7%	0.3%	2
2008. 12	48.0%	51.9%	0.0%	2
2008. 13	57.6%	42.3%	0.1%	1
2008. 14	56.5%	43.5%	0.0%	1
2008. 15	98.3%	1.7%	0.0%	1
2008. 16	97.2%	2.8%	0.1%	1
2008. 17	96.8%	3.1%	0.1%	1
2008. 18	0.0%	0.0%	100.0%	3

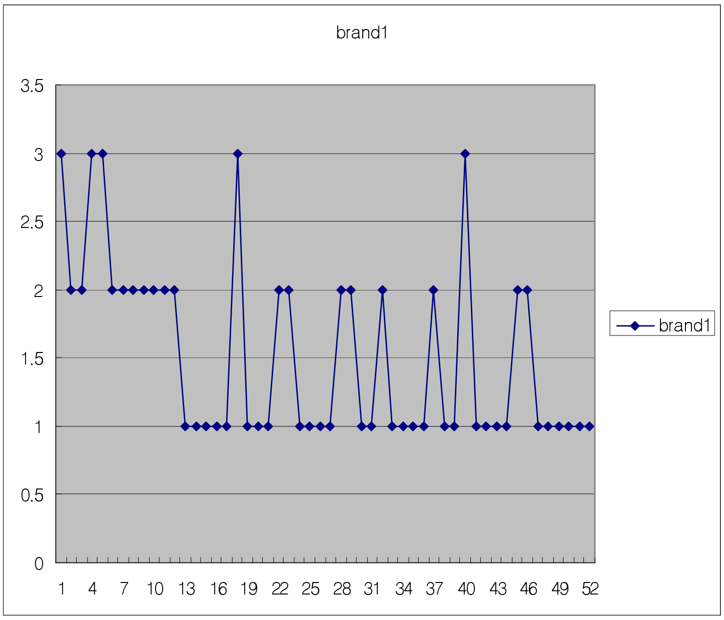

Figure 1. Volatility of Brand 1 for a year (x axis: week, y axis: brand power level)

In individual brands changes in brand power are appeared by segment. For instance, in case of Brand 1 it has the highest brand power in segmentation market 3, yet has the most poor brand power in segment market 1.

Thirdly, it is process through distribute to know which equitation among each multinomial logit model of the second stage is appropriate to which week. The following Table 2 shows some results of Brand 1 in the first half of the year 2008

For example, in week 1 of 2008 brand 1 displays that revenue is calculated by equitation of segment 3. The equitation of segment 3 is no included in week 2 of 2008, but explains segment 2, which shows revenue should be calculated. In other words, brand power of Brand 1 in segment 3 has been just lasted 1 week, yet that of Brand 1 in the segment 2 has been just maintained 2 week later on.

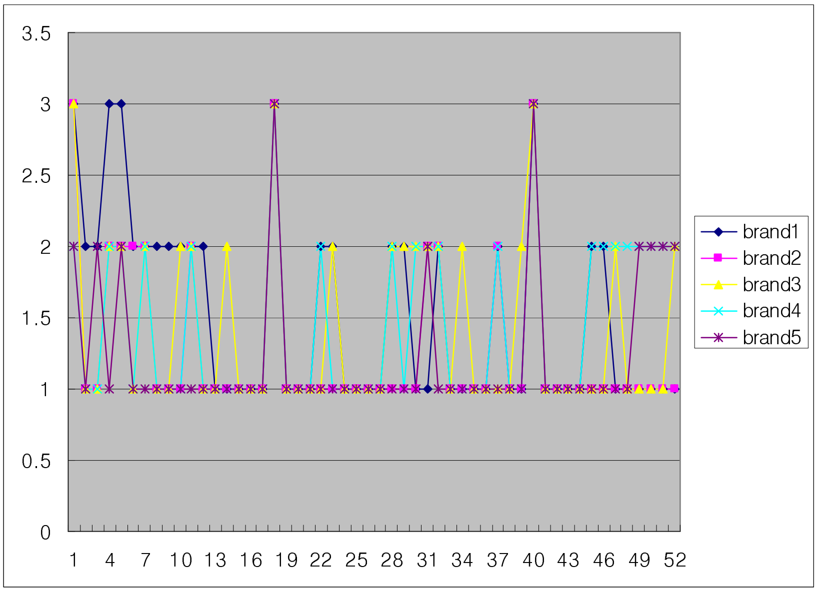

Figure 2. Volatility for each brand ((x axis: week, y axis: brand power level)

If the process above is coupled with rest 4 brands, it is as Figure 2. At figure, periods brand power is high or low are different in each brand. Consequently, marketing tools marketers of each brand employ are totally different by time to time

Technical difference about lasting time of brand power of each brand is existed. At Table 3 Brand 1 is more frequent than others in terms of long-standing brand power. On the other hand, it is rare to become the lowest brand power. In addition, with respect to changing frequency of brand power Brand 3 is large, while that of Brand 5 is small, especially Brand 5 often lasts low brand power.

The outcomes earned by designing this dynamic brand equity chaser model can be summarized as follows. First, different brand powers are derived by different aspects of high-demand and low-demand seasons and active and dull seasons. Marketers can trace the brand powers that appear differently in a low-demand season and in a certain period that all promotion concentrates.

Secondly, different brand powers are derived by regions in China. Therefore, brand power chaser model should be made for each region.

Thirdly, different brand powers are derived by size and type even in the same group of product. For example, as for the sizes of TV like 32 inches or 40 inches, different degrees of brand loyalty and different price and promotion elasticities are derived in the same market. Therefore, brand power chaser model should be applied to product line as well as product category.

Table 3. the brand dynamics of brand power

	Brand 1	Brand 2	Brand 3	Brand 4	Brand 5
Low level (1) weeks	30	41	33	31	42
Middle level (2) weeks	17	8	15	19	8
High (3) level week	5	3	4	2	2
No. of brand power level change	18	13	23	20	12

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