The Dynamics of Brand Value in the Carbonated Soft Drinks Industry

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PRELIMINARY

Abstract

This study examines how brand values of different carbonated soft drink (CSD) products change over time and how advertising and social media exposure contribute to brand building. The model consists of two stages. In the first stage, we adopt a structural approach to estimate the brand equities of 12 CSD products and measure the brand values in a Bertrand-Nash equilibrium. In the second stage, we study the impacts of marketing-mix variables on brand values. The empirical results show that both advertising expenditure and the quality of social media activity are important to brand value while the increase in the total social media activity has little effect.

Keywords: Carbonated soft drinks, Social media, Advertising

JEL classification: D12, L66, M37

1 Introduction

Brand equity is one of the most important intangible assets of firms. Large amounts of resources are spent on building and managing brand equity every year. In this study, we adopt a two-step approach to examine how the use of advertising and social media affects brand value. Specifically, we use a random coefficients logit model (Berry, Levinsohn and Pakes, 1995) to capture the dynamics of brand equities and estimate the model using observational data from the carbonated soft drinks (CSDs) market.

Sales of CSDs have been declining since 2005 (Beverage Digest, 2012), while demand for liquid refreshment beverage are shifting towards low caloric alternatives, such as bottled water. In order to maintain the profitability of their products, CSD manufactures such as Coca-Cola and PepsiCo improve their channel efficiency and reinvest the money saved from operational costs in the areas of marketing and brand building (Elliott, S., 2012).

Advertising is of prime importance to brand building. It contributes to both the awareness and goodwill stock of brands. Furthermore, we also take into account the impact of social media campaign on brand value in this study. Social media can facilitate product recommendation and reinforce brand loyalty, which is continuously getting significant for marketers and academia. The leader of the CSD industry, the Coca-Cola Company, has been shifting its emphasis from traditional advertising to online social media and Coca-Cola has become the most popular brand in the food and beverage sector on Facebook (Liu & Lopez, 2013). Given the recent growth of the social media use, it is attractive to examine the effect of social media marketing and compare to the traditional advertising on the dynamics of brand equity.

The paper is organized as follows. Section 2 describes the data. Section 3 introduce the empirical approach and section 4 presents the estimation and simulation results followed by conclusion in Section 5.

2 Data

This study combines three brand level data sets obtained from the Zwick Center for Food and Resource Policy at the University of Connecticut. The first one is the monthly Nielsen Scan Track data on CSD sales in 12 Designated Market Areas (DMAs) in the U.S. from 2011 through 2012. The data contain dollar sales, volume sales, and prices for major CSD brands. The second data set is the brand level advertising expenditure data obtained from Kantar media, covering the same periods as in the sales data. The last data set is the social media data collected from Facebook. It records all firm activities on brands homepages, including the photos, videos, events, and links posted, and the number of reactions following each activity, such as likes, comments, and shares. We aggregate the social media data to monthly level and combine it with the sales and advertising data for estimation. Figure 1 shows the advertising and Facebook activity of the top 2 regular soda brands.

To implement the random coefficients logit model, we augment the combined data with product characteristics (e.g. sugar) which are collected from nutrition labels on product packages. The market size is defined as the product of per capita consumption of soda and the population in each DMA. The corresponding market shares are computed by dividing the sales volumes by market size. Table 1 summarizes the prices, market shares, and attributes of different soda brands.

3 Framework

Before introducing the empirical model, we need to define the measure of brand value. We follow the definition in Goldfarb, Lu & Moorthy (2009) which sets brand value as the difference between the profit earned by a product in the real world and the profit it would have earned in its unbranded state. A product without brand equity in the counterfactual equilibrium only retains its search attributes, such as sugar, caffeine, and sodium in our case, while a branded product has marketing effects associated with its brand in addition. For example, a bottle of "unbranded Coca-Cola"—without the red color, the contour bottle, or the logo—may not be able to have the same imagery

as a branded one.

3.1 Stage 1: Demand Side

In the demand estimation stage, we use a random coefficients discrete choice model following the framework of BLP (1995). The indirect utility that consumer i derives from consuming product j in market t is

$$U_{ijt} = X_j\beta_i - \alpha_i P_{jt} + \xi_j + \zeta_{jt} + \varepsilon_{ijt}, \tag{1}$$

where X_j is the matrix of search attributes, P_{jt} is the vector of prices, β_i and α_i are consumer-specific coefficients, ξ_j is the unobserved product characteristic, ζ_{jt} is the demand shock in each market, and ε_{ijt} is an i.i.d error term. We normalize the utility from purchasing an outside alternative to zero.

The coefficients are assumed to be normally distributed as follows:

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Sigma\nu_i, \qquad \nu_i \sim N(0, I) \tag{2}$$

where β and α are the mean parameters, Σ is the scaling matrix, and ν is drawn from a normal distribution. We assume the i.i.d error term ε_{ijt} follows a type I extreme value distribution, and the market share of brand j in market t can be expressed as follows

$$s_{jt} = \int \frac{exp(X_j\beta_i - \alpha_i P_{jt} + \xi_j + \zeta_{jt})}{1 + \sum_{k=1}^{J} exp(X_j\beta_i - \alpha_i P_{jt} + \xi_j + \zeta_{jt})} \mathrm{d}P(\nu). \tag{3}$$

3.2 Stage 1: Supply Side

We assume that firms play a Nash-Bertrand pricing game in the CSD market. The profits of firm f are given by:

$$\pi_f = \sum_{j \in \mathcal{G}_f} (p_j - mc_j) M s_j(p) - C_f \tag{4}$$

where mc_j is the marginal cost of product j, M is the market size, C_f is the fixed cost, and $s_j(p)$ is the market share of product j which has been derived from the demand side. Under the Bertrand-Nash assumption, firms choose prices to maximize their profits, which leads to a set of first-order conditions:

$$s_j(p) + \sum_{l \in \mathcal{G}_f} (p_l - mc_l) \frac{\partial s_l(p)}{\partial p_j} = 0 \tag{5}$$

Using this set of first-order conditions, we calculate the prices in the counterfactual equilibrium without brand equity which in turn can be used to derive brand values.

3.3 Stage 2: Effects of Ad and Social Media on Brand

Following the Nerlove-Arrow model (Nerlove and Arrow, 1962), we specify the correlation between brand value and marketing-mix variables of advertising and social media as follows

$$\Delta\pi_{jt} = \gamma_0 + (1-\delta)\Delta\pi_{jt-1} + \gamma_1 ln(1 + A_{jt}) + \gamma_2 \frac{ln(1 + r_{jt})}{ln(1 + M_{jt})} \tag{6}$$

where $\Delta\pi_{jt}$ is the brand value of brand j at time t, A_{jt} is the advertising expenditure, M_{jt} is the number of firm activity on Facebook, r_{jt} is the number of consumer response to the activity, γs are the parameters to be estimated, δ is the depreciation rate, and the semilog transformation of advertising expenditure and Facebook activity are used to capture the diminishing returns. Although a typical firm in our sample increasingly engaged in social media activities from 2011 to 2012, consumer response did not follow the same pattern. We use the ratio of response to activity to capture the "efficiency" or the "quality" of Facebook activity which can reflect the effectiveness of social media exposure.

3.4 Estimation

We use the Nested Fixed Point (NFP) algorithm to estimate the first stage demand model. The product characteristics are assumed to be uncorrelated with unobservables, but the prices are endogenous. We use the average price in other markets as instrumental variables (Hausman, 1997;

Nevo, 2001). The errors from the first stage estimation will propagate to the second stage and we solve this problem by using an adjusted least square procedure.

4 Results

The demand estimates are shown in Table 2, Panel A. The deviations are significant, which indicates the presence of consumer heterogeneity. Price coefficient is negative as expected and sugar content also has a negative impact. We believe that the public is getting aware of the negative outcomes of excessive sugar and began to derive disutility from it. The mean value of brand equity estimates are shown in the Panel B of table 2. Popular brands such as Coca-Cola and Pepsi enjoy higher equity values. This result can explain why some brands hold larger market shares although the prices and ingredients of most CSD products are similar. Figure 2 illustrates the time trend in the brand equities for 6 popular brands.

Given the estimates of demand parameters, brand values are derived under Nash-Bertrand equilibrium assumption in the CSD industry. The mean and time trend of brand values are shown in table 2, Panel B, and Figure 3 respectively. Not surprisingly, strong brands help firms possess higher profits which emphasize the importance of brand building.

Table 3 shows the estimation results of the second stage. Brand values do depreciate over time and advertising as well as social media efficiency has positive impacts on brand values. We do not find a significant correlation between brand value and the number of firms' Facebook activity. The implication of this result is that the quality of what a firm posts on social media is more important than the volume of activities. Firms need to improve their social media efficiency to make their brands healthier.

5 Conclusion

Brand equity can affect a firm's performance in the marketplace. We use a two stage model to estimate the brand equity and brand value for 12 CSD brands and how advertising and social media

exposure influence the dynamics of brand value for those brands. The empirical results show that high brand quity is the determinant for high profits. We also find that solely concentrating on the volume of posts might not be an efficient way to follow for the purpose of building brands. Instead, firms need to pay more attention to the content of the message that they deliver through the social media platform.

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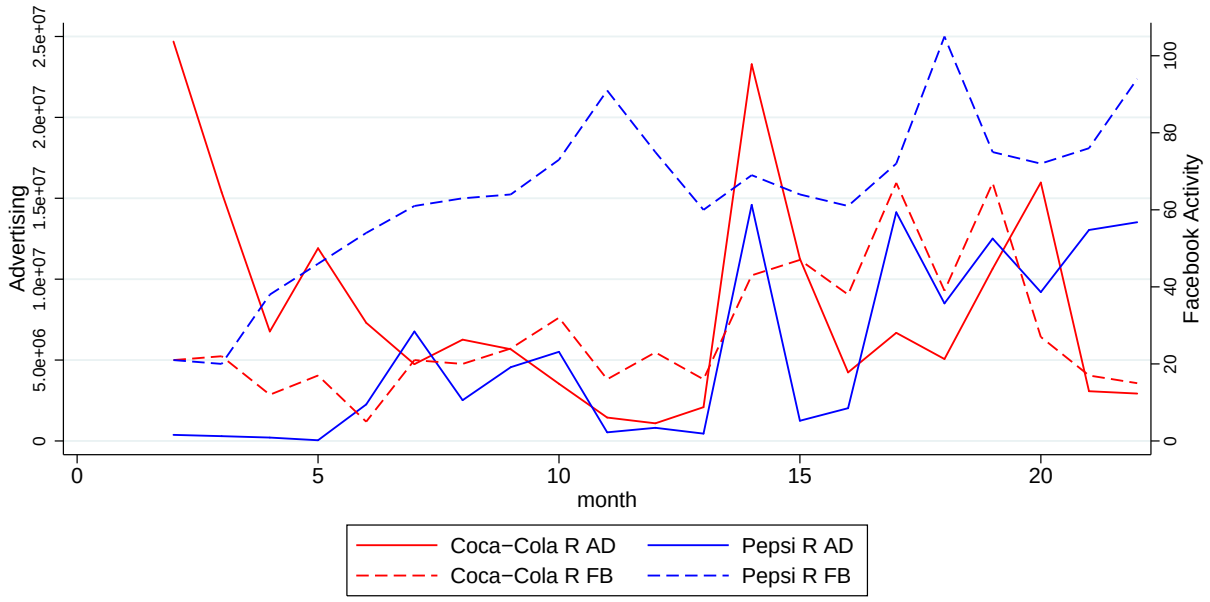

Figure 1: Ad and social media activity of top 2 regular CSD brands

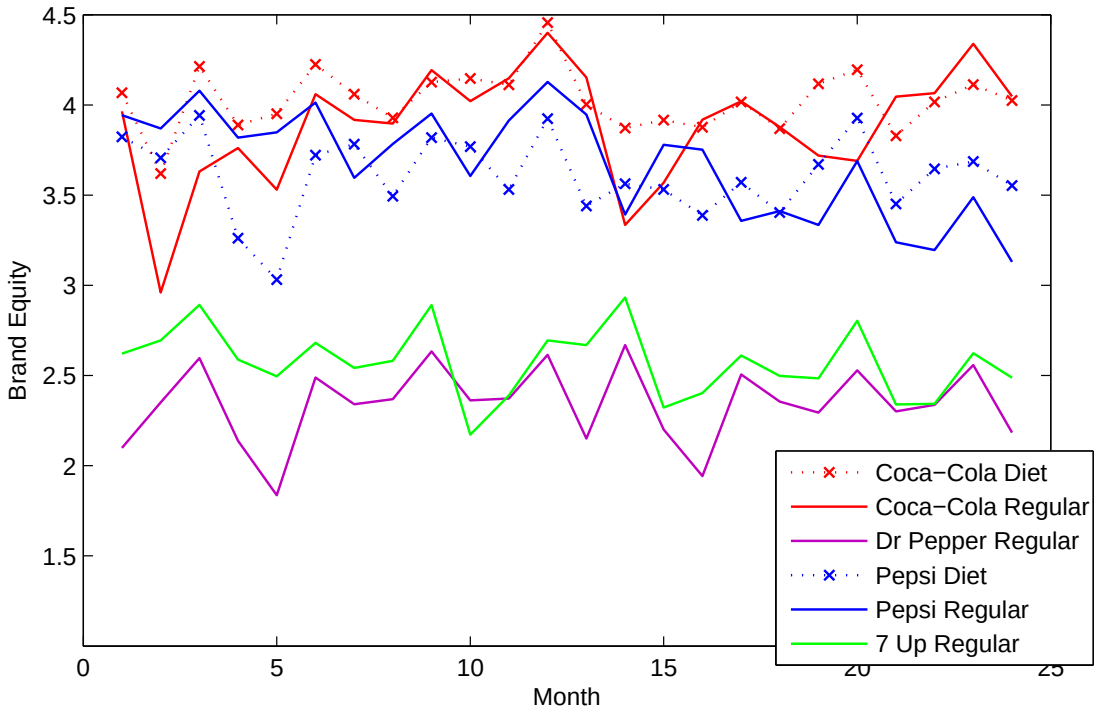

Figure 2: Brand Equities

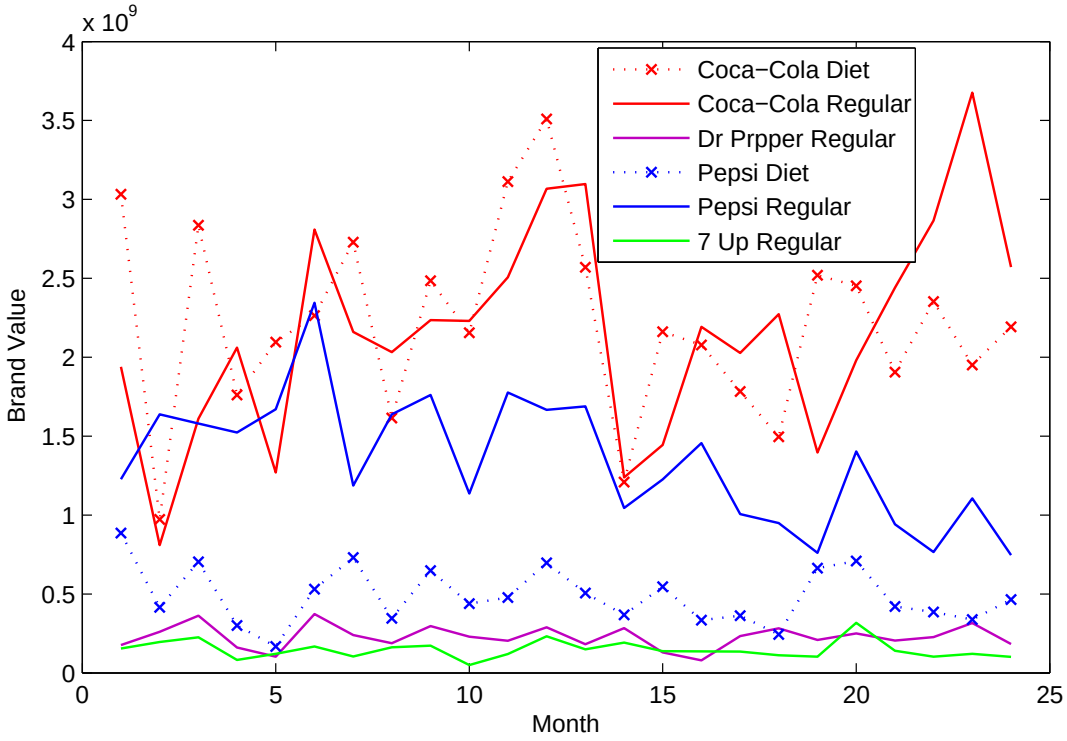

Figure 3: Brand Value

Brand	Price (cents/oz)	Shares %	Sugar (g/oz)	Sodium (mg/oz)	Caffeine (mg/oz)
Coca-Cola Diet	2.88	1.88	0	3.33	3.92
Coca-Cola Regular	2.81	3.11	3.25	4.17	2.92
Dr Pepper Regular	2.89	0.69	3.33	4.58	3.5
Fanta Regular	2.6	0.29	3.67	4.58	0
Mountain Dew Diet	2.75	0.34	0	4.17	4.5
Mountain Dew Regular	2.79	1	3.83	5.42	4.5
Pepsi Diet	2.64	1.25	0	2.92	2.92
Pepsi Regular	2.52	2.35	3.42	2.5	3.17
7 Up Regular	2.5	0.37	3.17	3.33	0
Sierra Mist Regular	2.51	0.27	3.25	3.17	0
Sprite Regular	2.86	0.85	3.17	5.83	0
Sunkist Regular	2.52	0.25	4.17	5.83	3.33

Table 1: Summary statistics

Panel A:

	Mean Utility		Deviations	
Variables	Means	Std. Err	Means	Std. Err
Price	-0.719	0.007	0.029	0.002
Sugar	-1.798	0.101	0.012	0.001
Sodium	0.037	0.001	0.022	0.001
Caffeine	0.328	0.019	0.072	0.002

Panel B:

Brand	Means of Brand Equity	Means of Brand Value (Million Dollars)
Coca-Cola Diet	4.027	2218.287
Coca-Cola Regular	3.886	2163.943
Dr Pepper Regular	2.343	227.616
Fanta Regular	3.696	490.528
Mountain Dew Diet	1.760	28.968
Mountain Dew Regular	3.125	1057.432
Pepsi Diet	3.610	486.880
Pepsi Regular	3.678	1343.365
7 Up Regular	2.573	147.237
Sierra Mist Regular	2.667	88.645
Sprite Regular	3.881	2068.878
Sunkist Regular	3.203	470.784

Table 2: Stage 1 Results

Varialbes	γ	Std. Err
Constant	-93.70	91.75
Advertising	7.83	3.8
Response Ratio	40.48	16.54
Depreciation	0.17	0.03

Table 3: Stage 2 Results