Brand Evaluation and Advertising Effects
- A Study of The Mobile Phone Industry

Bo Huang
The Ross School of Business
University of Michigan

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Introduction

- Research Objectives
- Motivation/Literature Review
- Intuition
Research Objectives

- Develop a quantitative method of estimating firms’ monetary brand values under dynamic Bertrand competition, and apply the method to the mobile phone industry in Italy.

- Extend the BLP’s framework by identifying the economic meaning of the latent variable $\xi$ in the utility/demand function of the discrete random coefficients logit model.

- Study the dynamics among firms’ advertising, brand and market shares.
Motivation/Literature Review

- Estimating the monetary value of brands remains a challenging task of utmost importance to business and academia. Two current approaches have their limitations:
  - The subjective judgment approach is just subjective. For example, it is based on people’s scoring.
  - The marketing costs approach may not reflect the true marketing effectiveness to the brand. For example, its advertising may address the wrong segments and do not increase any brand value.

- Tobin’s q is a method reflecting some unmeasured or unrecorded assets of the company.

- BLP(1995) first model and estimate the latent variable $\xi$ in the utility/demand function. Their major contribution rests on smartly solving endogeneity problems and enabling more reasonable price elasticity calculation.

- Nevo (2000a, b, 2001) applies their approach to the cereal industry, and writes a "How-to" paper on this method.
Intuition

- Apply the BLP method to estimate the latent variable $\xi$’s for all products by time period (i.e. market by market).
- Obtain the brand level $\xi$’s by calculating the average/market-share-weighted $\xi$ for each brand in each time period.
- Put all competitors’ advertising, $\xi$’s and market share in a time series setting, and estimate a Structural Vector Autoregressive Model (SVAR) $\Rightarrow$ 2nd structural model taking into account competition dynamics.
- Recover unobserved marginal cost for each product under differentiated products Bertrand competition.
- Manipulate a firm’s brand effects, recalculate the new scenario market shares for all competitors given all other variables constant, and calculate the firm’s profit change (loss) $\Rightarrow$ the brand monetary value for each period $\Rightarrow$ long-run brand value.

bohuang@umich.edu
Theoretical Framework

- Utility Function
- Demand Function
- Detrand Competition and Constant Marginal Cost
- Structural Vector Autoregressive Model
Utility Function

An individual’s utility function is defined as:

$$\ln(u_{ijt}) = X \theta(i) + \xi_{jt} + \epsilon_{ijt} \equiv U_{ijt},$$  \hspace{1cm} (1)

where $X$ is a Matrix of product characteristics.

$$\xi_{jt} = \xi_{bt} + \tau,$$  \hspace{1cm} (2)

where $\xi_{jt}$ and $\xi_{bt}$ are product and brand level latent variables, respectively. $\tau$ is error.

The parameters of an individual $i$’s utility function are:

$$\theta(i) = \bar{\theta} + \Pi D(i) + \Sigma \nu(i), \quad \nu(i) \sim P_0, \quad D(i) \sim PD,$$  \hspace{1cm} (3)

The utility of outside goods is normalized:

$$\ln(u_0) = 0, \quad \text{i.e.} \quad u_0 = 1.$$  \hspace{1cm} (4)

Therefore, the log-linear utility function can be written as:

$$U_{ijt} = \delta_{jt} \left( x_{jt}, \xi_{jt}; \theta_1 \right) + \mu_{ijt} \left( x_{jt}, \xi_{jt}, \nu(i), D(i); \theta_2 \right) + \epsilon_{ijt},$$  \hspace{1cm} (5)

$$\delta_{jt} = x_{jt} \theta_1 + \xi_{jt}, \quad \mu_{ijt} = x_{jt} \left( \Pi D(i) + \Sigma \nu(i) \right),$$

where $\delta_{jt}$ is the linear part and $\mu_{ijt}$ the non-linear part of the log utility function.
Conditional on $\nu(i)$ and $D(i)$ and after integrating out over $\epsilon$, which is assumed to have the Type I extremely value distribution, the conditional market share (i.e. the expected probability of individual $i$ choosing product $j$) is:

$$s_{ij}(x, \delta, \nu(i), D(i); \theta_2) = \frac{e^{(\delta_j+\mu_j)}}{1 + \sum_{q=1}^{J} e^{(\delta_q+\mu_q)}},$$

(6)

where $\mu(.)$ contains corresponding $\nu(i)$ and $D(i)$. The remaining two levels of integrals can be computed by Monte Carlo simulation as follows:

$$s^*_j(x, \delta, P_0, \hat{P}_D; \theta_2) = \frac{1}{ns} \sum_i s_{ij}(x, \delta, \nu(i), D(i); \theta_2),$$

(7)

where $ns$ is the number of simulated individuals in a market, and * indicates a simulation value.
Betrand Competition and Constant Marginal Cost

A firm $f$ maximizes its profit over its product portfolio, i.e. over all of its products in a market, by setting product prices. The profit function of firm $f$ is:

$$
\Pi_f = \sum_{j \in \mathcal{S}_f} (p_j - mc_j) M s_j (x, \xi, P_0, P_D; \theta),
$$

(8)

where $M$ is market size. There is a unique equilibrium that can be identified by solving the first order conditions for all products in a market:

$$
s_j (x, \xi, P_0, P_D; \theta) + \sum_{r \in \mathcal{S}_f} (p_r - mc_r) \frac{\partial s_r (x, \xi, P_0, P_D; \theta)}{\partial p_j} = 0.
$$

(9)

The marginal cost can be recovered as:

$$
mc \equiv p - \Delta(p, x, \xi, P_0, P_D; \theta)^{-1} s(p, x, \xi, P_0, P_D; \theta),
$$

(10)

where $\Delta$ is the matrix of $\partial s/\partial p$. 

bohuang@umich.edu  
Brand Evaluation and Advertising Effects
The SVAR is set up to reflect the following points:

- Advertising is a function of its own lags and lagged market shares.
- Consumers’ willingness-to-pay for a brand, $\xi_{bt}$, is a function of its own one-period lagged value and the contemporaneous advertising, i.e. all the past advertising is absorbed in $\xi_{b,t-1}$.
- Market share is a function of its own lag, and contemporaneous willingness-to-pay.
Structural Vector Autoregressive Model (SVAR)

Formally, the structural model is:

\[(\psi_0 - \psi_1 L - \psi_2 L^2 - \psi_3 L^3)Y_t = c + \Sigma v_t, \quad \text{(11)}\]

\[
\begin{bmatrix}
  l_{0,11} & 0 & 0 \\
  \psi_{0,21} & l_{0,22} & 0 \\
  0 & \psi_{0,32} & l_{0,33}
\end{bmatrix}
\begin{bmatrix}
  ad_{b,t} \\
  \xi_{b,t} \\
  s_{b,t}
\end{bmatrix}
= \begin{bmatrix}
  \overline{ad}_b \\
  \overline{\xi}_b \\
  \overline{s}_b
\end{bmatrix} +
\begin{bmatrix}
  \psi_{1,11} & 0 & \psi_{1,13} \\
  \psi_{1,21} & \psi_{1,22} & \psi_{1,23} \\
  0 & \psi_{1,32} & \psi_{1,33}
\end{bmatrix}
\begin{bmatrix}
  ad_{b,t-1} \\
  \xi_{b,t-1} \\
  s_{b,t-1}
\end{bmatrix}
+ \begin{bmatrix}
  \psi_{2,11} & 0 & 0 \\
  \psi_{2,21} & 0 & 0 \\
  0 & 0 & 0
\end{bmatrix}
\begin{bmatrix}
  ad_{b,t-2} \\
  \xi_{b,t-2} \\
  s_{b,t-2}
\end{bmatrix}
+ \begin{bmatrix}
  l_{0,11} & 0 & 0 \\
  0 & l_{0,22} & 0 \\
  0 & 0 & l_{0,33}
\end{bmatrix}
\begin{bmatrix}
  v_{ad,t} \\
  v_{\xi,t} \\
  v_{s,t}
\end{bmatrix}.
\]

It can also be written as follows with the underlined reduced form model:

\[
\psi_0(l_K - \phi_1 L - \phi_2 L^2 - \phi_3 L^3)Y_t = \psi_0 \omega_t + \psi_0 e_t \equiv c + \Sigma v_t \quad \text{(12)}
\]
Research Context and Data

- Italian Mobile Phone Industry and Market
- Data Description
- Data Processing
Italian Mobile Phone Industry and Market

- Italy is the 2nd largest European mobile phone market after Germany. Mobile phone penetration rate has been more than 100% for years.
- Competition is getting intensive all the time in both new product development and marketing.
- More importantly, mobile phone (handset) purchases are not bundled with the mobile phone service contract in Italy. Different from bundled markets such as USA, its industry structure provide researcher with clear handset price.
- There are dozens of mobile phone brands in the Italian market. The major players are Nokia, Samsung, Motorola, Sony-Ericsson, Simens and LG. They are the study subjects in this paper.
Data Description

I use four types of data:

- Self-collected product characteristics data from various Internet sources such as the web sites of mobile phone manufacturers, www.gsmarena.com and other public web sites\(^2\).

\(^2\) Special thanks to the Ross School of Business for financing the data collection, and to the excellent research assistant work by Guiling Wang and Jun Chen.
Data Processing

Price and volume data:

- I removed products whose agency-recorded market shares are less than 0.01%.
- Two products are removed because of obvious data input error (the unit prices are greater than Euro 2000).
- Another two products are removed because they are car phones, not belonging to the mobile phone handset category.

Voting scores:

- If there are less than two missing data points, they are filled with the average of the adjacent available data points as the mobile phone models adjacent in a product series are very similar in their characteristics and design.
Data Processing

Data Summary

- 60 time periods (markets)
- 6 brands
- 479 mobile phone models
- 7798 observations
- 2 voting scores
- 72 time-period Advertising data of all brands
- 9 + 6 phone characteristics incl. price

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Brand Evaluation

- "Design" and "Feature" as A Function of Phone Characteristics
- Efficient GMM
- Brand Effects
- Brand Monetary Values
"Design" and "Feature" as A Function of Phone Characteristics

- Design voting scores data enable me to control for intangible/hard-to-measure product characteristics.
- Both voting scores can be written as a function of exogenous product characteristics. In other words, their corresponding fitted values are the linear combinations of those characteristics.
- Therefore those fitted values of design and feature voting scores can be used as independent variables for parsimonious estimation.
- As both design and feature scores are continuous on [1, 10], they also improve the practicality of non-linear search of the GMM algorithm.
"Design" and "Feature" as A Function of Phone Characteristics

Table: Estimated Parameters of The Design and Feature Functions

<table>
<thead>
<tr>
<th>Variable</th>
<th>Design Coef.</th>
<th>SE</th>
<th>Feature Coef.</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>11.744</td>
<td>1.094</td>
<td>3.512</td>
<td>1.292</td>
</tr>
<tr>
<td>Form</td>
<td>0.190</td>
<td>0.042</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Extra display</td>
<td></td>
<td></td>
<td>0.155</td>
<td>0.055</td>
</tr>
<tr>
<td>Lnlength</td>
<td>−0.768</td>
<td>0.216</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lnwidth</td>
<td></td>
<td></td>
<td>0.852</td>
<td>0.337</td>
</tr>
<tr>
<td>Lnheight</td>
<td>−0.378</td>
<td>0.115</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Email</td>
<td></td>
<td></td>
<td>0.137</td>
<td>0.062</td>
</tr>
<tr>
<td>Internet</td>
<td>0.346</td>
<td>0.075</td>
<td>0.448</td>
<td>0.085</td>
</tr>
<tr>
<td>Connectivity</td>
<td>0.157</td>
<td>0.034</td>
<td>0.297</td>
<td>0.044</td>
</tr>
</tbody>
</table>

Note: All p-values are less than 0.03.
### Efficient GMM

**Table:** Estimated Parameters of Utility Function

<table>
<thead>
<tr>
<th>Variable</th>
<th>1st Stage Coef.</th>
<th>2nd Stage Coef.</th>
<th>SE</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>−7.7884</td>
<td>0.1053</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Price</td>
<td>−1.0661</td>
<td>0.0023</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Form</td>
<td>0.1367</td>
<td>0.0023</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Extra display</td>
<td>0.1785</td>
<td>0.0011</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Lnlength</td>
<td>−1.2335</td>
<td>0.0098</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Lnwidth</td>
<td>3.9008</td>
<td>0.0159</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Lnheight</td>
<td>0.0602</td>
<td>0.0059</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Email</td>
<td>−0.1216</td>
<td>0.0012</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Internet</td>
<td>0.2073</td>
<td>0.0069</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>Connectivity</td>
<td>0.4529</td>
<td>0.0069</td>
<td>0.0000</td>
<td></td>
</tr>
<tr>
<td>( \nu )</td>
<td>0.464</td>
<td>0.4723</td>
<td>0.6923</td>
<td>0.2476</td>
</tr>
<tr>
<td>Price ( \times \nu )</td>
<td>0.2824</td>
<td>0.2857</td>
<td>0.0034</td>
<td>0.0000</td>
</tr>
<tr>
<td>Design ( \times \nu )</td>
<td>0.6744</td>
<td>0.674</td>
<td>0.0251</td>
<td>0.0000</td>
</tr>
<tr>
<td>Feature ( \times \nu )</td>
<td>0.2691</td>
<td>0.2704</td>
<td>0.0261</td>
<td>0.0000</td>
</tr>
<tr>
<td>GMM obj. value</td>
<td>781.2140</td>
<td>154.9452</td>
<td>200</td>
<td>200</td>
</tr>
<tr>
<td>num. of simulation</td>
<td>200</td>
<td>200</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

bohuang@umich.edu  
Brand Evaluation and Advertising Effects
Willingness-To-Pay For Different Brands

Time

Willingness-To-Pay

brand1
brand2
brand3
brand4
brand5
brand6
Demeaned Willingness-To-Pay For Different Brands

Willingness-To-Pay

Time

0 10 20 30 40 50 60

-2 -1.5 -1 -0.5 0 0.5 1 1.5

brand1
brand2
brand3
brand4
brand5
brand6
• Recall $\hat{\xi}_{jt}$ were calculated in a context in which each time period was regarded as a market.

• However, we can see from the first figure that $\hat{\xi}_{bt}$ exhibit clearly a time series correlation and a clear annual cycle, and that

• the relative positions of each brand remain relatively stable and change gradually.

• After demeaning the industry average of $\hat{\xi}_{jt}$, we can see a clearer trend, which accurately reflect the reality of the industry.

• Those two figures confirm that $\hat{\xi}_{bt}$ do have a lot of information that remains to be exploited.
Brand Effects

Run SVAR estimation with three major brands out of six, and obtain the brand effects after controlling the serial correlation and advertising effects. The brand effects, i.e. $\bar{\xi}$’s are:

$$\bar{\xi}_1 = 1.3769$$
$$\bar{\xi}_2 = 1.7306$$
$$\bar{\xi}_3 = 1.8330$$

Next I lower the brand effects to their lower bound for each of those three firms separately, and calculate the profit changes for all six firms.
Profit Changes When The Effects Of Brand 2 Are Lowered

- brand1
- brand2
- brand3
- brand4
- brand5
- brand6

Profit, Euros

Time

Profit, Euros

-4
-6
-8
-10
Profit Changes When The Effects of Brand 3 Are Lowered
Table: Long-Run Brand Monetary Values At Different Discount Rates, million Euros

<table>
<thead>
<tr>
<th>Discount rate</th>
<th>Brand1</th>
<th>Brand2</th>
<th>Brand3</th>
</tr>
</thead>
<tbody>
<tr>
<td>5%</td>
<td>5,024.6</td>
<td>12,413.0</td>
<td>3,806.3</td>
</tr>
<tr>
<td>10%</td>
<td>2,512.3</td>
<td>6,206.5</td>
<td>1,903.1</td>
</tr>
<tr>
<td>15%</td>
<td>1,674.9</td>
<td>4,137.6</td>
<td>1,268.8</td>
</tr>
<tr>
<td>20%</td>
<td>1,256.2</td>
<td>3,103.2</td>
<td>951.6</td>
</tr>
<tr>
<td>25%</td>
<td>1,004.9</td>
<td>2,482.6</td>
<td>761.3</td>
</tr>
</tbody>
</table>
This paper has developed a new quantitative method in evaluating brands’ monetary value in a dynamic competition setting, which is close to the real business world. The empirical work confirms the validity and accuracy of the method.

- It estimates a more "pure" brand effect not only by removing the effects of products and advertising effects but also by controlling the serial correlation and effects of competitors’ advertising.
- It also contributes to the literature in simplifying a complex panel, abstracting the key relationship in a dynamic time series setting, and enabling a deeper analysis on economic and marketing questions.