Distance Metric or Random Coefficients Logit? A Comparison of Product-level Demand Models Using Chinese Instant Noodle Scanner Data

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Abstract: Estimation of product-level demand is essential to understanding consumer food purchase behavior. The objective of this paper is to compare the performance of the Distance Metric model (DM model) and the Random-coefficients discrete-choice demand model (BLP model) in modeling Chinese consumer demand for instant noodles. Both the DM and BLP model allow for relatively flexible substitution patterns across products and avoid the curse of the dimensionality problem associated with having many products. Nevertheless, the two models have their strengths and weaknesses. For example, the DM estimation is linear and therefore can handle any number of products. The cross-price effects are limited by observed attributes. The BLP model may provide more flexible substitution effects but is highly nonlinear and constrained by the number of products it can manage in real-world settings. Considering the popularity and importance of the two alternative methods in consumer demand research, it is surprising no research has compared the performance of the two models. To fill this gap, we compare the performance of the BLP model and the DM model in modeling consumer demand using both in-sample and out-of-sample model comparison methods with a unique Chinese scanner dataset from a sample of 40,000 urban households in 20 Chinese provinces and 4 megacities.

Keywords: Instant noodle demand, BLP model, Distance metric demand model, Chinese scanner data.

Introduction

Estimation of product-level demand is essential to understanding consumer food purchase behavior. There are two nontrivial concerns when estimating demand for a large number of differentiated products with various attributes. One is a large number of parameters to be estimated. For example, in an unrestricted product-level demand system, there are n^2 price coefficients, where n is the number of products. Even if we impose symmetry, homogeneity, and adding-up restrictions, the dimension of the parameter space is still too large to estimate for any system with more than a few dozen products. Another problem is the heterogeneity[1] in consumer tastes. We would observe the individual taste differentiation in the modern marketplace and therefore require different demand patterns.

The random-coefficients discrete-choice demand model (BLP model) (Berry, 1994; Berry et al., 1995) and Distance Metric model (DM) are two popular solutions to avoid the curse of dimensionality (e.g., having many products), as well as to allow for relatively flexible substitution patterns across products. Nevertheless, the two models have their strengths and weaknesses.

Discrete-choice models can solve the dimensionality problem by projecting the products onto a space of characteristics, making the relevant dimension the dimension of this space rather than the square of the number of products, and offering the possibility of uncovering rich substitution patterns with a limited number of parameters. Additionally, discrete-choice models are available for modeling product substitutions within a category (e.g., Nevo 2001).

[1] Models that do not address this issue when demand is modeled using a "representative" consumer, per capita demand, or highly restrictive utility functions (Lopez and Lopez, 2009).

Heterogeneity is modeled explicitly and unknown parameters governing the distribution of heterogeneity are estimated (Nevo, 2000a). The BLP model, which is superior to prior logit and nested logit discrete-choice models, has gained considerable importance in empirical work. It incorporates random coefficients for continuously product characteristics which creates potentially more flexible substitution patterns. Additionally, it allows for consumer heterogeneity in the price parameter (Grigolon and Verboven, 2014), deals with the endogeneity of prices, and produces more realistic demand elasticities. However, BLP is computationally more demanding and constrained in the number of products that it can manage in a real-world setting (Dubé, Fox, & Su, 2012; Judd & Skrainka, 2011).

Another approach, the DM model, solves the dimensionality problem by casting the n^2-dimensional price effects into the lower dimensional product attribute space. In contrast to discrete-choice models, the DM model allows consumers to purchase any number of products within the budget constraint. Additionally, the cross-price effects in DM models are determined by multiple product attributes. Most DM models are linear in parameters—a desirable property in light of recent findings of numerical difficulties in estimating some nonlinear discrete-choice models (Dubé, Fox, and Su 2012; Knittel and Metaxoglou 2014) and therefore can handle any number of products. Nevertheless, a weakness of DM models is that the cross-price effects are limited by the observed attributes specified by the researcher which implies the importance to use a comprehensive list of product attributes to reduce this bias.

Considering the popularity and importance of the two alternative approaches above in consumer demand research, it is surprising that no studies has compared the performance of the two models. To fill this gap, the objective of this paper is to compare the performance of DM model and the BLP model in modeling Chinese consumer demand for instant noodles. To evaluate the performance of the two models, we use model forecast accuracy as the sole selection criterion (Naert P, Weverbergh M, 1981).

We also contribute to the literature by being the first to estimate instant noodle demand and the extent of products differentiation on the China market. We use a unique Chinese scanner dataset collected by Kantar Worldpanel from a sample of 40,000 urban households in 20 Chinese provinces and 4 megacities. Focusing on the products from 9 top instant noodle brands will allow us to look more closely at the consumer choices on instant noodle products.

Demand Model

Random-coefficients discrete-choice demand model (BLP model)

In the BLP model, a consumer chooses an instant noodle brand product from competing products to maximize the utility, which is driven by the brand characteristics as well as his/her own preferences. Assume there are $t = 1,\ldots,T$ markets, each with $i = 1,\ldots,I_t$ consumers. We use $j = 1,\ldots,J$ to denote each instant noodle product, where *j*=0 to denotes the general outside products in the instant noodle market.

The indirect utility of consumer *i* from consuming instant noodle product *j* in market *t* is represented by

$$u_{ijt} = \alpha_i(y_i - p_{jt}) + x_{jt}\beta_i + \xi_{jt} + \varepsilon_{ijt} \qquad i = 1,\ldots,I_t, \qquad t = 1,\ldots,T, \qquad j = 1,\ldots,J \quad (1)$$

where y_i is the income of consumer *i*, p_{jt} is the price of instant noodle product *j* in market *t*, x_{jt} is the nutritional characteristics of product *j*, ξ_{jt} is the unobserved product characteristics, and ε_{ijt} is a mean-zero stochastic term distributed independently and identically as Type I extreme value distribution. Consumer *i* can choose to buy the outside product with normalized utility $u_{i0t} = \alpha_i y_i + \varepsilon_{i0t}$.

The unobserved characteristics are captured by the error term. Relying on the data structure, some unobserved characteristics can also be captured by dummy variables. For example, we can model $\xi_{jt} = \xi_j + \xi_t + \Delta\xi_{jt}$ and capture ξ_j and ξ_t by brand- and market-specific dummy variables.

β_i and α_i are modeled as following:

$$\begin{pmatrix} \alpha_i \\ \beta_i \end{pmatrix} = \begin{pmatrix} \alpha \\ \beta \end{pmatrix} + \Pi D_i + \Sigma \nu_i \qquad \nu_i \sim P_\nu(\nu), \quad D_i \sim \widehat{P}_D(D) \quad (2)$$

where D_i are demographic variables, ν_i captures the unobserved individual characteristics (e.g. attitude of health, health status, etc.), $P_\nu(\cdot)$ is a parametric distribution, $\widehat{P}_D(\cdot)$ is either a nonparametric distribution known from other data sources or a parametric distribution with the parameters estimated elsewhere.

Let $\theta = (\theta_1, \theta_2)$, $\theta_1 = (\alpha, \beta)$ and $\theta_2 = (\Pi, \Sigma)$ contain the linear and nonlinear parameters, respectively. Thus, we have,

$$\begin{aligned} u_{ijt} &= \alpha_i y_i + \delta_{jt}(x_{jt}, \xi_{jt}, p_{jt}; \theta_1) + u_{ijt}(x_{jt}, p_{jt}, \nu_i, D_i; \theta_2) + \varepsilon_{ijt} \\ \delta_{jt} &= x_{jt}\beta - \alpha p_{jt} + \xi_{jt} \qquad u_{ijt} = \left[-p_{jt}, x_{jt}\right](\Pi D_i + \Sigma \nu_i) \end{aligned} \quad (3)$$

where δ_{jt} is referred to as the mean utility, which is common to all consumers, and $u_{ijt} + \varepsilon_{ijt}$ represent a mean-zero heteroskedastic deviation from the mean utility, which captures the effects of the random coefficients.

A basic assumption is that consumers purchase one unit of the instant noodle product that gives the highest utility. Let A_{jt} defines the individuals who choose one brand product *j* in market *t*, where $A_{jt}(x_{\cdot t}, p_{\cdot t}, \delta_{\cdot t}; \theta_2) = \left\{(D_i, \nu_i, \varepsilon_{i0t}, ..., \varepsilon_{iJt}) \mid u_{ijt} \geq u_{ilt} \quad \forall l = 0,1,..., J\right\}$, $l = 0$ denotes the outside good.

The market share of the j^{th} brand is an integral over the consumers in the region A_{jt}, given by

$$s_{jt}(x_{\cdot t}, p_{\cdot t}, \delta_{\cdot t}; \theta_2) = \int_{A_{jt}} dP(D,\nu,\varepsilon) = \int_{A_{jt}} dP(\varepsilon \mid D,\nu) dP(\nu \mid D) dP_D(D) = \int_{A_{jt}} dP_\varepsilon(\varepsilon) dP_\nu(\nu) d\hat{P}_D(D)$$

(4)

where $P_\varepsilon(\varepsilon)$, $P_\nu(\nu)$, and $\hat{P}_D(D)$ are population distribution functions, assumed to be independent of each other. The price elasticities of the market shares are given by:

$$\eta_{jkt} = \frac{\partial s_{jt}}{\partial p_{kt}} \cdot \frac{p_{kt}}{s_{jt}} = \begin{cases} -\dfrac{p_{jt}}{s_{jt}} \displaystyle\int \alpha_i s_{ijt}(1-s_{ijt}) d\hat{P}_D(D) dP_\nu(\nu) & if \quad j = k, \\ \dfrac{p_{kt}}{s_{jt}} \displaystyle\int \alpha_i s_{ijt} s_{ikt} d\hat{P}_D(D) dP_\nu(\nu) & if \quad otherwise, \end{cases} \quad (5)$$

where $s_{ijt} = \exp(\delta_{jt} + u_{ijt}) / [1 + \sum_{k=1}^{K} \exp(\delta_{kt} + u_{ikt})]$

The price sensitivity is a now a probability-weighted average and can differ over products. As such, the model allows for flexible patterns of substitution that are more likely to be observed in the data (Vincent, 2015).

The direct effects of sodium and fat contents which are defined as sodium elasticity and fat elasticity on brand-level demand are measured by

$$\in_{jkt} = \frac{\partial s_{jt}}{\partial Sodium_{kt}} \cdot \frac{Sodium_{kt}}{s_{jt}} \quad (6)$$

$$\in_{jkt} = \frac{\partial s_{jt}}{\partial Fat_{kt}} \cdot \frac{Fat_{kt}}{s_{jt}} \quad (7)$$

where $Sodium_{kt}$ and Fat_{kt} measure sodium and fat contents for brand *k* in market *t*. The signs of sodium and fat elasticity are uncertainty since they depend on the taste of consumers.

The method for the market share forecast bases on Vincent (2015): We use Monte Carlo integration with R random draws[2] of (D_i and v_i) from the distributions $P(D_i)$ and $N(0, I_{K+1})$.

$$s_{jt} = \frac{1}{R}\sum_{i=1}^{R} P_{ijt} = \frac{1}{R}\sum_{i=1}^{R} \frac{\exp\{\delta_{jt} + (x_{jt}^{'}, p_{jt})(\Pi D_i + Lv_i)\}}{1+\sum_{m=1}^{J}\exp\{\delta_{jt} + (x_{jt}^{'}, p_{jt})(\Pi D_i + Lv_i)\}} \quad (8)$$

Distance Metric Model

The linear approximate version of Deaton and Muellbauer's (1980) almost ideal demand system (AIDS) is the most popular functional form adopted in DM models. Assuming weak separability between instant noodle products and the numéraire good, we can use two-stage budgeting to characterize consumer preferences for instant noodle products.

In the first stage, the consumer allocates budgets between instant noodles and a *numéraire* good representing all other goods and services. Using the almost ideal demand (AID) system (Deaton and Muellbauer 1980), the first-stage decision can be written as

$$w_{nht} = a_{nht} + r_{nn}\ln p_{nht} + r_{no}\ln p_{oht} + b_n \ln(y_{ht} / p_{ht}) \quad (9)$$

Where w_{nht} is the budget share of instant noodles in market *h* and period *t*; p_{nht} is the price index for instant noodles (denoted by subscript *c*) as a category; p_{oht} is the price index for the

[2] We set R=200 in this paper, according to Vincent (2015).

numeraire good[3] (denoted by subscript o); y_{ht} is per capita income; and a, r, and b are parameters. The cost-of-living index p_{ht} is defined as

$$\ln p_{ht} = a_0 + a_{nht} \ln p_{nht} + a_{oht} \ln p_{oht} + 0.5\left\{ r_{nn}(\ln p_{nht})^2 + r_{oo}(\ln p_{oht})^2 \right\} + r_{no} \ln p_{nht} \ln p_{oht} \quad (10)$$

where $a_{oht} = 1 - a_{nht}$, $r_{oo} = 0 - r_{no}$ by the adding-up condition, and $r_{no} = 0 - r_{nn}$ by the homogeneity condition. We augment the intercept a_{nht} as follows to account for market, time, a seasonal effects:

$$a_{nht} = a_{n0} + \sum_{j=2}^{24} c_{nj} \times province_{jht} + \sum_{k=2}^{13} g_{nk} \times qw_{kht} + v_{nl} \times yr_{lht} \quad (11)$$

Where mk_{jht} , qw_{kht} , and yr_{lht} are binary indicator variables for market *j* (out of a total of 30 markets), the kth period (out of a total of 13 four-weekly periods) of a year, and year *l* (reference year=2011), respectively, and a_{n0}, c_{nj} , g_{nk} , and v_{nl} are parameters.

The Stone price indices p_{nht} and p_{oht} may be endogenous because they use current budget shares as weights. We used the loglinear analogue of Laspeyres prices (Moschini 1995) for the instant noodle group and the *numéraire* good as instruments. The budget share equation (10) and the two instrumental variable equations for $\ln p_{nht}$ and $\ln p_{oht}$ were estimated jointly using full information maximum likelihood (FIML).

[3] The price index for the numeraire good was obtained by solving $\ln CPI_{ht} = w_{nht} \ln p_{nht} + w_{oht} \ln p_{oht}$ for p_{oht} , where CPI is the consumer price index for all goods and services. (Zhen et al., 2014)

In the second stage, the consumer chooses among instant noodle products conditional on total expenditures allocated to instant noodles from the first-stage decision. We used the following linear approximate AID to model product-level instant noodle demand:

$$w_{iht} = a_{iht} + \gamma_{ii} \ln p_{iht} + \sum_{j \neq i} \gamma_{ijht} \ln p_{jht} + \beta_i \ln(x_{ht} / p_{nht}) \quad (12)$$

Where w_{iht} is the budget share of product *i* (out of a total of *N* products) in market *h* and period *t*; p_{jht} is the price of instant noodle product *j* normalized by its sample mean (Moschini 1995); x_{ht} is per capita instant noodle expenditure, $\ln p_{nht} \equiv \sum_{j \in N_{ht}} w_{jht} \ln p_{jht}$ is the Stone price index for instant noodles as a category, N_{ht} is the set of instant noodle products sold in market *h* and period *t* and varies over market and time due to product entry and exit, γ and β are parameters.

To account for demand heterogeneity across products, markets, seasons, and over time, the demand shifter a_{iht} is augmented to include product-specific trends:

$$a_{iht} = \phi_{ih} + \sum_{l=1}^{N} \theta_l \times z_{li} \times trend_{ht} \quad (13)$$

Where ϕ_{ih} is the fixed effect for instant noodle product *i* in market *h*; $trend_{ht}$ is a linear time trend; z_{li} is an indicator variable for product *l*; equal to 1 if $l = i$ and 0 otherwise; and the θ_l terms are parameters. By including product-specific market and trend effects, equation (13) controls for a wide range of heterogeneities that, if unaccounted for, may result in biased estimates of price coefficients.

DM demand model (Pinkse, Slade, and Brett 2002; Pinkse and Slade 2004) is one solution to the curse of dimensionality is that restrict substitutions across products, as a function of their distance in the attribute space. Zhen, Brissette, and Ruff (2014) modified the standard DM model to incorporate product heterogeneity into the cross-price effects and demonstrated the superiority of the modified DM model over the standard model in a non-nested model comparison test. We extend their modified DM model to account for the effect of market share differences on the cross-price effect between products that share observed attributes. This extension generates more realistic cross-price effects between products close to the observed attribute space but distant in market share.

We specify the cross-price coefficient γ_{ij} in equation (4) as

$$\gamma_{ijht} = \sum_{m=1}^{M} w_{i0} w^{*}_{0mijht} (d_{0m} + d_{1m} D_{ij} + d_{2m} Dij^{2}) \quad (14)$$

With $D_{ij} = \dfrac{1}{1 + 2\,|\,(w_{i0} - w_{j0}) / (0.5(w_{i0} + w_{j0}))\,|}$ (15)

where M is the number of observable product attributes, w_{i0} is product *i*'s base budget share set at its sample mean, and d_{0m}, d_{1m}, d_{2m} are parameters. If the m^{th} attribute is discrete (e.g., bag package or not), let $w^{*}_{0mijht} = w_{j0}\kappa_{mij} / \omega_{0miht}$, $\omega_{0miht} = w_{i0} + \sum_{k \in N_{ht}} w_{k0}\kappa_{mik}$, such that κ_{mij} is a binary variable equal to 1 if products *i* and *j* ($j \neq i$) have the same level/description in the m^{th} attribute (e.g., both bag-packed instant noodle products) and 0 otherwise (including the case $\kappa_{mij} = 0$). Following Zhen, Brissette, and Ruff (2014), the w_{i0} term is included in ω_{0miht} to preserve the symmetry condition $\gamma_{ijht} = \gamma_{jiht}$. If the m^{th} attribute is multiple level (e.g., sodium content), let $w^{*}_{0mijht} = w_{j0} / (1 + 2 | c_{mi} - c_{mj} |)$, where c_{mi} and c_{mj} are values of the continuous attribute for products *i* and *j*, respectively.

The term D_{ij} in equation (15) is key to our extension of the DM model. It is inversely related to the difference in base budget share between products *i* and *j*. We use D_{ij} and its power series expansion to quantify the cross-price elasticity between products close in the M observed attributes but distinct in market share, the latter of which may be driven by such less quantifiable factors as brand equity and tastes, among others. Finally, it is important to note that although the cross-price effects are restricted to be functions of distances in the attribute space, the own-price coefficients γ_{ii} and category expenditure coefficients β_i are unrestricted in estimation.

In this model, the cross-price effects are restricted to be functions of distances in the attribute space, the own-price coefficients and category expenditure coefficients are unrestricted in estimation.

Forecast accuracy

Forecast accuracy is accessed by calculating three measures of predictive ability: Root-mean-square deviation (RMSE), and U, the multi-brand version of Theil's (1967) inequality coefficient proposed by Naert and Weverbergh (1981).

U statistics is a global measure of prediction accuracy given that several brands are considered.

$$U = \frac{\sqrt{\sum_{j=1}^{n}\sum_{t=1}^{T}(s_{jt} - s_{jt})^2 / nT}}{\sqrt{\sum_{j=1}^{n}\sum_{t=1}^{T}s_{jt}^{\;2} / nT} + \sqrt{\sum_{j=1}^{n}\sum_{t=1}^{T}s_{jt}^{\;2} / nT}}$$

Where s_{jt} is the market share of product *j* in period *t* and s_{jt} is the related predicted market share, n is the total number of products, T is the number of observations in the prediction sample, i.e., observations in 2013. Specifically, I normalize the market shares as: $\tilde{s}_{jt} = s_{jt} / (\sum_{j=1}^{n} s_{jt})$ by market in order to make the sum of the market share is equal to 1 in each market.

Kullback-Leibler divergence (KL). The Kullback-Leibler divergence is used as a goodness-of-fit measure or as a prediction accuracy measure (see Haaf et al.,2014; Morais et al., 2016). It is a sum of the log-ratios between the observed values and the fitted values of the shares, weighted by the observed value. The log-ratio allows to take into account the relative error, and the weight emphasizes the importance of large errors in large shares.

$$KL(s, \hat{s}) = \sum_{t=1}^{T}\sum_{j=1}^{J}\log\left(\frac{s_{jt}}{s_{jt}}\right)s_{jt}$$

Empirical Analysis

A. Chinese Instant noodle market

The instant noodle market in China is a matured noteworthy market. It accounts for nearly half of the world's total consumption (Zhu, 2015). Instant noodle industry in China unlike other developing economies is largely controlled by few Cooperatives and Independent Instant Noodles companies. For a company without a good distribution network and brand awareness, it will be difficult to compete in Chinese Instant noodles market.

Historically, instant noodles have been preferred to other convenience foods when eating time is constrained, especially for college students and migrant workers (Sun et al, 2015; Park et al., 2011; Jin, 2013). In recent years, the occurrence of food security issues led to a variety of toxic rumors about instant noodles, pushed instant noodles into the cusp of public opinions. Instant noodles were considered as junk food mainly because of being cooked in oil, a preservative, with high calories included and containing little nutrition. Therefore, the industry of instant noodles in the Chinese market suffered a serious defeat. In 2015, the production volume of instant noodles was 32.6 billion in the mainland. In the past 2 years production volume has declined 8.54 percent a year, and revenue has fallen by 6.75%. Therefore, exploring the demand of instant noodles and consumers' preference is key to better understanding this market.

B. Dataset for the Chinese instant noodle market

To examine the effectiveness of the two models, we use a unique Chinese scanner data from Kantar Worldpanel. The dataset is stratified by market, income, and Universal Product Code (UPC) number from 2011 to 2013. It includes UPC-specific information, such as instant noodle weighted purchase volume and weighted expenditure. The household-level data we use tracks Chinese urban households in 20 provinces and 4 megacities. The Kantar Worldpanel dataset is supplemented with a nutrition database[4]. Combining the two we use the UPCs to create a nutrition profile of each household's instant noodle purchases.

The market in this paper is defined using a combination of province, year and four-weekly periods (province-quad-week). From prior studies, market size can be set equal to the number of households in the economy (e.g. Berry et al., 1995), or parameterized using market-level data characteristics (such as population) that vary across markets (e.g. Berry, 1990). In this paper, the market size is calculated as annual per capita consumption of instant noodles[5] (34 packs) multiplied by the number of households and average household size in the data[6] within each market.

We consider 9 top instant noodle brands in terms of market share in the Kantar dataset. Each instant noodle market comprises a large number of products that individually account for small shares of the market. To limit the number of products in the demand model and to preserve as much of the product differentiation as possible, we created unique products by aggregating similar items based on brand, flavor and package shape.

More specifically, we separate instant noodle products into to four general flavors: Beef, pork, chicken and seafood. In terms of packaging, we separate the products into two categories: "bag" packaged or "other". The observed characteristics of instant noodles estimated in the sample include price, serving size (weight per pack), and nutritional components[7]: energy, protein, carbohydrate, fat and sodium. Particularly, we use mean values of the same product from other markets to impute missing nutritional components.

4 The nutrient contents information is collected from manufacturers' websites.
5 Source: http://sc.sina.com.cn/health/ysbj/2012-05-22/092938041.html
6 Source: http://www.stats.gov.cn/tjsj/pcsj/
7 I normalized the nutritional components to 100 grams (equal to nearly 1 pack of instant noodle).

Table 1 lists the summary statistics of the instant noodle brands we consider. The sample contains 26354 observations based on 39 4-weekly (Quad week) periods (2011 to 2013) and 936 markets in total. The prices of instant noodle brands considered from mainland are about $20 per kilogram, while imported brands (Brand 7) are generally twice as expensive. Assuming a 2000 kcal/day diet, per 100g instant noodles provide about 24% of daily energy requirement assuming no food waste, nearly reach the recommended sodium daily value (2.4 g), and one third of the fat daily value (65g) (Crasto, 2013). Notably, instant noodles are very high in saturated fat, which has been proved as a main cause of heart diseases (De Souza, Russell J., et al., 2015; Praagman, Jaike, et al., 2016).

Table 1 Product Summary Statistics

Brand	Sample size	Price (RMB/100g)	Market share (%)	Serving size (g)	Sodium (g/100g)	Energy (KJ/100g)	Protein (g/100g)	Carbohydrate (g/100g)	Fat (g/100g)
Brand1	7230	2.67	2.50	99	1.91	1916.69	8.23	55.00	23.11
Brand2	3256	2.11	1.16	111	2.27	1997.37	9.40	62.21	21.06
Brand3	4199	2.58	1.21	90	2.05	1859.51	8.57	51.86	22.20
Brand4	2292	1.79	0.75	94	2.42	1980.16	8.65	56.56	22.77
Brand5	2273	1.80	0.30	97	1.92	1724.27	7.28	55.15	21.24
Brand6	2554	1.67	0.10	98	0.96	2035.84	7.80	62.00	22.30
Brand7	1983	4.80	0.13	93	1.27	1858.71	9.36	57.28	23.42
Brand8	1620	2.38	0.26	99	1.92	1621.34	10.73	68.98	7.36
Brand9	947	1.08	0.52	97	2.34	2001.55	9.73	62.08	21.09

Notes: 1. Results are averages of all markets in the 2011–2013 period.

2. Serving size is rounded to the nearest integer.

We introduce some unobserved characteristics as fixed effects including instant noodle brand, province/megacity, and quad-week dummy variables (Nevo, 2001). Particularly, brand-specific dummy variables capture the characteristics that do not vary by market, making the correlation between prices and the unobserved quality is fully accounted (Nevo, 2000a).

To calculate prices of the instant noodle products, we construct the Fisher ideal price index for product j which is calculated as

$$p_{hjt} = \sqrt{\frac{\sum p_{iht} q_{i0}}{\sum p_{i0} q_{i0}} \frac{\sum p_{iht} q_{iht}}{\sum p_{i0} q_{iht}}} \quad (16)$$

where p_{iht} and q_{iht} are the price and purchase quantity of product *i* for household *h* in market *t*, respectively, and p_{i0} and q_{i0} are the base price and base quantity of *i* set at their national means.

Price is potentially endogenous since retail price effects rely on observed and unobserved consumer and product characteristics, and their variations lead to price changes (Lopez et al., 2015). The instrument for each household-specific price index is calculated as the weighted average of the price of the same product from all other provinces in the same period, here a period is defined as year-quad-week combination. The inverse of the distance between the capital city of two provinces is used as the weight. The method to instrument endogenous prices is valid under the identifying assumption that province specific valuations are independent across all provinces after controlling for household demographic effects and brand specific means (Nevo, 2000b; Zhen et.al.,2013). Besides, we also use interactions of price index and nutritional components as additional instruments to help identify random coefficients and increase estimation efficiency.

Considering the purpose of this article, and for simplicity and tractability, we do not include sociodemographic characteristics and treat deviations from the mean parameters as idiosyncratic random errors similar to Lopez et al. (2015) and Tiboldo et al. (2016). We conducted all estimations in Stata 13.1 (Vincent, 2015). The results are presented in the following section.

Results and Discussion

This section shows the estimation results of the two demand models. We use 2011 and 2012 data to run the BLP model and get the demand estimation results including instant noodle elasticities. Furthermore, we use the 2013 data to do out of sample forecast of the instant noodle product market share. The results are as follows.

Table 2 shows the coefficients estimation results of the BLP model. Overall, the results seem plausible in terms of signs and expected coefficients. Nearly all key parameter estimates in Table 2 are statistically significant at the 1% level. As expected, consumers have a negative and strong valuation of price. All of the nutritional attributes are significant, specifically, consumers have a positive and significant valuation of sodium and fat, the two main ingredients that affect instant noodle taste. From a nutritional standpoint, excess consumption of sodium and fat in the diet is designated as unhealthy, thus the positive coefficient might reflect preferences for what is perceived as an average preference for flavor over nutritional or obesity concerns. Additionally, consumers also have a positive and significant valuation of energy, but the effect is not big. On the contrary, consumers have negative valuation of protein and carbohydrates. Lastly, the demand of chicken flavor instant noodle products is significantly less than other flavors.

Using the Brand 1 as a benchmark, results for brand fixed effects show that consumers have a lower intrinsic valuation of other instant noodle brands, regardless of product characteristics. Further econometric results show that, on one hand, the preferences for instant noodle products vary by province, while on the other hand, preferences vary in different 4-week periods.

Table 2. Demand estimation results

Variable	Mean utility Coefficient	S.E.		Mean utility Coefficient	S.E.
Attributes			Provinces		
Price	-2.904***	(1.029)	BeiJing	1.235***	(0.360)
Sodium	1.899***	(0.0901)	ChongQing	0.0423	(0.207)
Energy	0.000722***	(0.000108)	FuJian	-0.0250	(0.246)
Protein	-0.223***	(0.0228)	GuangDong	-0.356	(0.311)
Carbohydrate	-0.0165**	(0.00805)	GuangXi	-0.739**	(0.332)
Fat	0.0869***	(0.0113)	GuiZhou	-0.563	(0.380)
Chicken flavor	-0.893***	(0.0388)	HeBei	1.685***	(0.406)
Brands					
2	-1.084***	(0.0774)	HeNan	0.943***	(0.287)
3	-1.106***	(0.0495)	HeiLongJiang	0.739***	(0.159)
4	-2.064***	(0.0779)	HuBei	-0.436**	(0.170)
5	-1.805***	(0.0625)	HuNan	-0.789***	(0.264)
6	-1.032***	(0.0939)	JiLin	0.927***	(0.183)
7	-0.969***	(0.0808)	JiangSu	0.0798	(0.108)
8	0.177	(0.161)	JiangXi	-0.300**	(0.138)
9	-1.793***	(0.0927)	LiaoNing	0.790***	(0.204)
Time effects: 4-weekly period					
QW2	0.179**	(0.0799)	ShaanXi	0.540***	(0.121)
QW3	0.166**	(0.0756)	ShanDong	0.642***	(0.172)
QW4	-0.0727	(0.0712)	ShanXi	2.356***	(0.609)
QW5	-0.243**	(0.103)	ShangHai	0.711***	(0.151)
QW6	-0.304**	(0.137)	SiChuan	-0.978***	(0.259)
QW7	-0.337***	(0.119)	TianJin	1.070***	(0.264)
QW8	-0.172**	(0.0837)	YunNan	-0.282	(0.184)
QW9	-0.0982	(0.0708)	ZheJiang	-0.0753	(0.0815)
QW10	-0.0780	(0.0719)	constant	-6.358***	(1.001)
QW11	-0.0653	(0.0622)	Random coefficient		
QW12	0.0488	(0.0646)	Price SD	1.489	(1.067)
QW13	0.0588	(0.0643)	Sodium SD	5.23e-09	(0.585)
Observations	18208				

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This paper selects in total 9 top instant noodle brands and 51 products. All own-price elasticities of demand were negative and all cross-price elasticities positive. The magnitude of the own-price elasticities ranges from -1.517 for brand 1 (Beef flavor with bag package) to nearly -2 for brand 9 (Seafood flavor with bag package). Since there are no prior studies estimating price elasticities of instant noodle in Chines market, the magnitudes of the own-price elasticities are similar to previously estimated elasticities of cakes and cookies (Own price elasticity= -1.697) demand using scanner data (Zhen et.al., 2013). Table 3 shows the price elasticities of demand for instant noodle products in these top 4 brands.

Generally speaking, brand 1 products have lower own-price elasticities, while brand 4 products have larger own-price elasticities. Considering instant noodle flavor, own-price elasticities of beef flavor is lower while their cross-price elasticity is larger, which shows that consumers prefer beef flavor, we can also see that the next one favorable flavor is pork. Consumers have brand loyalty to brand 1, the own-price elasticities of its products with all the package shapes are smaller than other instant noodle brands, and the cross-price elasticities are larger. For other brands, product choices are more responsive to changes in the price of instant noodle with bag package than other packages. This attests to a strong degree of brand loyalty when it comes to substitution across brands based on price changes alone.

In terms of cross-price elasticities, with the price of brand 1 and 2 increasing, the quantities of brand 4 are sold more. For brand 3 and 4, product choices are more responsive to changes in the price of the same brand than across brands.

Table 3. Price elasticities of demand for TOP 4 instant noodle brands, all provinces

	1% rise in Price											
Product	111	112	121	122	131	132	141	142	211	212	231	232
% change in												
111	-1.5166	0.0374	0.0140	0.0017	0.0222	0.0023	0.0146	0.0023	0.0418	0.0022	0.0137	0.0009
112	0.2403	-1.7146	0.0143	0.0017	0.0223	0.0023	0.0147	0.0023	0.0419	0.0022	0.0135	0.0009
121	0.2424	0.0372	-1.7508	0.0017	0.0222	0.0022	0.0147	0.0023	0.0421	0.0022	0.0136	0.0009
122	0.2460	0.0380	0.0151	-1.7496	0.0230	0.0024	0.0154	0.0023	0.0437	0.0023	0.0147	0.0009
131	0.2347	0.0368	0.0137	0.0017	-1.7277	0.0023	0.0147	0.0023	0.0391	0.0022	0.0131	0.0009
132	0.2248	0.0377	0.0135	0.0017	0.0222	-1.7345	0.0151	0.0024	0.0375	0.0021	0.0131	0.0009
141	0.2428	0.0371	0.0136	0.0016	0.0220	0.0022	-1.7439	0.0022	0.0422	0.0021	0.0136	0.0009
142	0.2399	0.0375	0.0143	0.0017	0.0222	0.0023	0.0152	-1.7511	0.0413	0.0021	0.0132	0.0009
211	0.2451	0.0378	0.0142	0.0017	0.0223	0.0023	0.0148	0.0022	-1.7038	0.0022	0.0138	0.0009
212	0.2452	0.0382	0.0144	0.0017	0.0227	0.0023	0.0153	0.0023	0.0446	-1.7750	0.0143	0.0009
231	0.2565	0.0368	0.0139	0.0016	0.0226	0.0020	0.0162	0.0023	0.0471	0.0022	-1.7540	0.0009
232	0.2524	0.0381	0.0133	0.0017	0.0230	0.0022	0.0173	0.0028	0.0455	0.0022	0.0148	-1.7605
311	0.2424	0.0381	0.0144	0.0017	0.0224	0.0023	0.0148	0.0023	0.0431	0.0022	0.0137	0.0009
312	0.2405	0.0384	0.0143	0.0017	0.0223	0.0023	0.0146	0.0023	0.0418	0.0022	0.0134	0.0009
331	0.2545	0.0377	0.0146	0.0017	0.0226	0.0021	0.0176	0.0023	0.0485	0.0023	0.0160	0.0009
332	0.1894	0.0414	0.0104	0.0015	0.0216	0.0033	0.0127	0.0026	0.0206	0.0015	0.0077	0.0008
341	0.2575	0.0374	0.0141	0.0017	0.0227	0.0021	0.0162	0.0024	0.0485	0.0021	0.0148	0.0009
342	0.1812	0.0428	0.0087	0.0013	0.0199	0.0031	0.0115	0.0029	0.0231	0.0014	0.0083	0.0007
411	0.2802	0.0373	0.0160	0.0017	0.0203	0.0017	0.0151	0.0020	0.0571	0.0023	0.0194	0.0010
412	0.2326	0.0406	0.0131	0.0016	0.0186	0.0015	0.0107	0.0019	0.0450	0.0027	0.0103	0.0008
421	0.2991	0.0379	0.0214	0.0019	0.0228	0.0015	0.0207	0.0023	0.0638	0.0029	0.0284	0.0010
422	0.2087	0.0342	0.0154	0.0021	0.0221	0.0011	0.0130	0.0020	0.0684	0.0038	0.0152	0.0005
431	0.2942	0.0364	0.0183	0.0017	0.0219	0.0015	0.0175	0.0021	0.0600	0.0024	0.0249	0.0010
432	0.2990	0.0354	0.0225	0.0018	0.0211	0.0010	0.0187	0.0020	0.0739	0.0041	0.0266	0.0011

Note: The values are median elasticity of all the markets.
Product number: The first number represents the brand.
The second number represents the flavor: 1= Beef, 2= Chicken, 3= Pork, 4= Seafood
The third number represents the package shape: 1= Bag, 2=Other shapes (Include barrel package, box package and cup package).

Table 4. Price elasticities of demand for TOP 4 instant noodle brands, all provinces (Continue)

		1% rise in Price											
% change in	Product	311	312	331	332	341	342	411	412	421	422	431	432
	111	0.0692	0.0089	0.0044	0.0007	0.0030	0.0005	0.0108	0.0010	0.0028	0.0003	0.0106	0.0007
	112	0.0704	0.0090	0.0044	0.0007	0.0031	0.0005	0.0112	0.0010	0.0028	0.0003	0.0106	0.0007
	121	0.0704	0.0088	0.0044	0.0007	0.0030	0.0005	0.0113	0.0010	0.0029	0.0003	0.0107	0.0007
	122	0.0708	0.0085	0.0046	0.0008	0.0030	0.0005	0.0104	0.0010	0.0029	0.0004	0.0113	0.0007
	131	0.0676	0.0092	0.0044	0.0007	0.0030	0.0005	0.0104	0.0010	0.0029	0.0003	0.0116	0.0007
	132	0.0663	0.0091	0.0044	0.0007	0.0030	0.0005	0.0088	0.0009	0.0027	0.0004	0.0099	0.0006
	141	0.0682	0.0086	0.0044	0.0007	0.0030	0.0005	0.0109	0.0010	0.0029	0.0003	0.0107	0.0007
	142	0.0693	0.0090	0.0044	0.0008	0.0031	0.0005	0.0106	0.0010	0.0029	0.0003	0.0107	0.0007
	211	0.0707	0.0088	0.0044	0.0007	0.0030	0.0005	0.0112	0.0011	0.0029	0.0003	0.0108	0.0007
	212	0.0698	0.0088	0.0045	0.0008	0.0031	0.0005	0.0114	0.0010	0.0028	0.0003	0.0110	0.0007
	231	0.0681	0.0082	0.0046	0.0007	0.0031	0.0005	0.0119	0.0009	0.0028	0.0003	0.0115	0.0006
	232	0.0696	0.0093	0.0046	0.0008	0.0031	0.0005	0.0096	0.0009	0.0027	0.0003	0.0088	0.0006
	311	-1.6804	0.0090	0.0044	0.0007	0.0031	0.0005	0.0111	0.0011	0.0029	0.0003	0.0108	0.0007
	312	0.0711	-1.7487	0.0044	0.0007	0.0031	0.0005	0.0110	0.0010	0.0028	0.0003	0.0107	0.0007
	331	0.0669	0.0079	-1.7801	0.0008	0.0030	0.0005	0.0120	0.0010	0.0030	0.0003	0.0125	0.0007
	332	0.0722	0.0124	0.0035	-1.5601	0.0040	0.0005	0.0046	0.0010	0.0014	0.0004	0.0017	0.0004
	341	0.0670	0.0087	0.0048	0.0007	-1.7879	0.0005	0.0115	0.0011	0.0028	0.0003	0.0117	0.0007
	342	0.0713	0.0127	0.0029	0.0009	0.0040	-1.6436	0.0055	0.0009	0.0016	0.0003	0.0024	0.0003
	411	0.0693	0.0076	0.0042	0.0005	0.0026	0.0004	-1.7911	0.0010	0.0028	0.0004	0.0123	0.0008
	412	0.0720	0.0110	0.0015	0.0006	0.0024	0.0004	0.0130	-1.7504	0.0038	0.0003	0.0159	0.0007
	421	0.0716	0.0068	0.0051	0.0005	0.0027	0.0005	0.0143	0.0010	-1.8381	0.0003	0.0144	0.0007
	422	0.0427	0.0054	0.0018	0.0005	0.0015	0.0007	0.0189	0.0008	0.0096	-1.8384	0.0575	0.0006
	431	0.0681	0.0063	0.0045	0.0005	0.0028	0.0005	0.0134	0.0010	0.0030	0.0003	-1.8006	0.0007
	432	0.0711	0.0059	0.0025	0.0005	0.0023	0.0004	0.0298	0.0017	0.0083	0.0004	0.0606	-1.9047

Note: the values are median elasticity of all the markets.

According to equation (8), we can predict the market share of instant noodle products in 2013, and compare it with the true market share values to see the power of prediction of BLP method.

$$s_{jt} = \frac{1}{R}\sum_{i=1}^{R} P_{ijt} = \frac{1}{R}\sum_{i=1}^{R} \frac{\exp\{\delta_{jt} + (x_{jt}^{'}, p_{jt})(\Pi D_i + L v_i)\}}{1 + \sum_{m=1}^{J} \exp\{\delta_{jt} + (x_{jt}^{'}, p_{jt})(\Pi D_i + L v_i)\}} \quad (17)$$

Where δ_{jt} is the BLP estimated mean utility, we know that $\delta_{jt} = x_{jt}\beta - \alpha p_{jt} + \xi_{jt}$, for unobservable ξ_{jt}, I select the values randomly from the estimated ξ_{jt} from the BLP estimation.

The result of prediction is as below:

Table 5 shows the comparison of true market shares and predicted values, the mean value of true market share is 0.012, and the predicted value is 0.010, which are very similar. The RMSE is 0.012, and the U statistics is 0.192.

Table 5 Summary of statistics of true and predicted market shares

	Market share	Predicted market share
Min	1.520E-5	2.273E-6
Max	0.288	0.359
Mean	0.012	0.010
STD	0.030	0.028
RMSE	0.012	
U statistics	0.160	

Conclusion

The BLP model shows that the magnitude of the own-price elasticities of instant noodle products ranges from -1.517 to nearly -2. Besides, consumers tend to have brand loyalty to leading brand products, especially for brand 1, the own-price elasticities of its products with all the package shapes are smaller than other instant noodle brands, and the cross-price elasticities are larger. Cross-price elasticities illustrate that brand choices are more responsive to changes in the price of the leading brands. In terms of flavor of instant noodle products, the own-price elasticities of beef flavor are lower, which shows that consumers prefer beef flavor, and the next one favorable flavor is pork.

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