Attention Economy in Online Daily Deals: Demand Estimation using Structural Models

Research-in-Progress

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Abstract

Online daily deal sites such as Groupon, which have grown explosively in recent years, allow merchants to gain the attention of online consumers and thereby increase their customer base. In this paper, we use structural models to estimate demand for a large daily deals site. We find that for a voucher with an average market share, a one per cent extension in the sale period is associated with a decrease in voucher demand by 0.22%. Moreover, a one per cent increase in the price is associated with a decrease in demand by 2.43%. Furthermore, the counter-factual experiment results show that, ceteris paribus, a one-day extension of the sale time period will decrease the product's weekly market share by 8.0%. This suggests the presence of attention economy in online daily deals such that limited-time offers are likely to draw the consumers' attention and consequently lead to additional sales.

Keywords: Online Daily Deal, Online Discount Voucher, Attention Economy, Structural Modeling, Random Coefficient Nested Logit, BLP

Introduction

Online daily deal sites such as Groupon, which have grown explosively in recent years, allow merchants to gain the attention of online consumers and thereby increase their customer base. ‘Deal-of-the-day’ websites, a form of electronic commerce, offer time-limited bargain deals with significant discounts—normally 50-90% off—for specific regions. Online daily deal sites send the information on deals to their subscribers via email and short messages, and consequently merchants are introduced to a number of new customers. The so-called “Groupon magic” has seen Groupon revenue grow from $15M in 2009 to $2.6B in 2013 (Marketwatch, 2014).

Several studies have examined the business model of daily deals from the perspective of coupons (Dholakia, 2011), price discrimination (Edelman et al., 2010), and social learning (Li and Wu, 2012). Wu et al. (2013) find through an analysis of Groupon sales data that purchases increase when the thresholds, that is, the number of deal purchases which are needed to activate the discount, are reached, and thus purchasing of deals becomes more active. Whereas, the study of Subramanian (2012) shows that consumers can wait strategically until the threshold is reached.

We assume that a daily deal site is an online marketplace in that it involves both supply and demand, despite the fact that daily deals differ from traditional commerce sites as they provide bargain deals for
limited time. Our goal in this study is to use structural models to estimate demand for vouchers analyzing the sales dataset of an online daily deal site. We examine how the observed and unobserved characteristics of heterogeneous products and consumers influence the demand for vouchers, specifically the effects of price, discount rate and sales period. The reason we use structural models is that endogeneity issues emerge with the correlations between the errors and observed variables in the reduced form models, since misspecification in general induces non-independent errors. Prices in general are likely to be correlated with the error term in the estimation of demand. Thus, the estimate of the price in this setting would be biased depending on the unobserved product characteristics (Nevo, 2001). Furthermore, daily deals are normally grouped into several predetermined categories, such as restaurants and bars, exhibitions, travel and beauty and spa. Consumer preferences towards the same category are likely to be correlated with one another.

This study addresses the price endogeneity issues intrinsic in demand estimation by building random coefficient demand models in line with the BLP (Berry et al., 1995) method. We use the price and sales dataset of one of the largest online daily deal site in Asia for a period of six months. Unlike traditional marketplaces, an increase in length of the sale time period in the online daily deal site is likely to decrease sales.

**Literature Review**

Our paper contributes to the literature on the emerging business of online daily-deals. Dholakia (2011) conducted a survey of small businesses partnering with Groupon, and several analytical models with descriptive statistics have been presented to explain daily deal economics and marketing strategy (Edelman et al, 2011; Byers et al., 2012; Kumar and Rajan, 2012; Li and Wu, 2012). Ye et al. (2011) show the dynamic patterns of purchasing times on the websites of Groupon and LivingSocial. Byers et al. (2012) empirically show that a negative side effect for Groupon’s merchants is that Yelp ratings decline from the merchants’ previous rating as a result of their partnership with Groupon. Li and Wu (2012) and Li (2013) measure the effects of observational learning and word-of-mouth (WOM) using a panel data set and regression discontinuity methods.

The limited time window for voucher sales is closely related with the concept of attention economy, first discussed by Davenport and Beck (2001). Attention becomes the limiting factor in the consumption of information as contents and products have grown increasingly abundant and available. There is an active stream of microeconomic research on how consumer choice is influenced by attention (Masatlioglu et al., 2012). From the viewpoint of sale models, Varian (1980) shows that retail stores decide the period of sales to price discriminate between informed and uninformed consumers. Online daily deals can be understood to behave in order to attract price-sensitive consumers. The empirical study of Pesendorfer (2002) finds that price sensitive consumers tend to wait for the sales, resulting in the increasing sales at the starting point of sales.

Our work is closely related to models of demand estimation in the differentiated product market. BLP proposes a new model considering the observed and unobserved characteristics of products using only market-level data and dealing with price endogeneity issues (Nevo, 2001). Its applications have been various, including studies on automobiles (Berry et al., 1995), books (Brynjolfsson et al., 2003; Ghose et al., 2006), newspapers (Fan, 2013), personal computers (Song, 2007) and cable TV (Goolsbee and Petrin, 2004). Dube (2004) apply the method to the situation for consumers to purchase multiple products and multiple units. The BLP method has also been adopted widely in demand estimation in IS literature (Ghose and Han, 2011; Ghose et al., 2012; Ghose and Han, 2014).

**Data and Research Design**

**Data**

We use a dataset consisting of list price, discount rate, discounted price, sales quantity, sales period and characteristics data from one of the largest online daily deal sites in Asia. The voucher categories in the dataset are restaurants and bars, exhibitions, travel and beauty and spa. The data set covers the six-month period from August 9, 2010, to January 29, 2011.
We have the sample of 1,165 deals for this study. Market Share is defined by total market size and outside good following the BLP method. In the sample, we assume that discrete choices of consumers are made weekly, while the total market size is inferred from the number of members in the daily deal site. List Price is the list price of deals and ranges from 0 to US$1,000 and averages US$70. Promotional coupons of large franchises tend to be provided either for free or at a low price. Discount Rate represents the discount rate and varies widely from 0% to 99%. However, over 97 percent of deals offer at least a 50-percent discount. Discounted Price is the price consumers actually pay. Minimum Sale is the specific number of sales units to trigger the discount rate available. The average minimum sale is 100, however, can be as low as 1 and as high as 5,000. Maximum Sale is the number of vouchers available for each deal, ranging from 30 to 99,999. Term of Validity denotes the number of days that purchasers are able to redeem their coupons. The average of Term of Validity is 85, but as low as 1 and as high as 1,826. Sale Period represents the number of days when consumers are able to purchase a coupon. More than 75% of deals are on sale for a maximum of 2 days. Sales Quantity is the number of vouchers sold per deal, ranging from 2 to 49,995.

Deals are classified into categories afterwards. Restaurants account for the largest category with 37%. Beauty and spa have 18%, followed by exhibition with 12%, café with 9%, bar with 8%, travel with 6%, and the remaining categories with 10%.

**Econometric Model**

We discuss our model based on the random coefficients nested logit (RCNL) model effective in estimating demand of the products grouped into predetermined categories. Utility function is defined as below following the identification of observed variables for products and consumers. Then we use the RCNL model derived by Grigolon and Verboven (2011). The RCNL combines the random coefficient logit model (BLP) and the nested logit model. In $t$ market ($t=1,...,T$), each consumer $i$ may either choose the outside good 0 or $j$ differentiated product ($j=0,...,J$). The random coefficients vector, $\beta_i$, can be specified as follows:

$$u_{ijt} = x_{jt}' \beta_i + \xi_{jt} + \bar{\epsilon}_{ijt},$$

where $\beta_i = \beta + \Sigma v_i + \Pi_1 D_{1it} + \Pi_2 D_{2it}$, $D_i \sim P_0^* (D), \nu_i \sim N(0, I)$

$$\bar{\epsilon}_{ijt} = \zeta_{igt} + (1 - \rho) \epsilon_{ijt},$$

where $x_{jt}$ is a $K \times 1$ vector of observed product characteristics (including sales period), $\beta_i$ is a $K \times 1$ vector of random coefficients capturing the individual-specific valuations for the product characteristics, $\xi_{jt}$ refers to unobserved product characteristics and $\bar{\epsilon}_{ijt}$ is a remaining individual-specific valuation for product $j$.

Let $\beta$ be a $K \times 1$ vector of mean values of the characteristics, $\sigma$ be a $K \times 1$ vector with standard deviations of the valuations, and $v_i$ be a $K \times 1$ vector with standard normal random variables. $\Pi$ is a $K \times 1$ vector with standard deviations of the valuations and $D_i$ is a $K \times 1$ vector with nonparametric demographic distribution (age and gender). We draw samplings ($D_i$) from age distribution using kernel density model with bandwidth 5. $\bar{\epsilon}_{ijt}$ can be modeled as iid random variables with an extreme value or logit distribution, as in BLP. Grigolon and Verboven (2011) suggest that the $\bar{\epsilon}_{ijt}$ follows a more general nested logit distribution, allowing preferences to be correlated across products in the same group or segment. This model can assign each product $j$ to a group $g$ ($g=0,...,G$). The groups are collectively exhaustive and mutually exclusive, and group 0 is reserved for the outside good 0. The $\bar{\epsilon}_{ijt}$ has iid extreme value and consequently, $\zeta_{igt}$ follows the unique distribution. The parameter $\rho$ is a nesting parameter ($0 \leq \rho \leq 1$), and can be interpreted as a random coefficient proxying for the degree of preference correlation between products of the same group. As $\rho$ approaches one, the within-group correlation of utilities approaches one, and consumers perceive products of the same group as perfect substitutes relative to other products. As $\rho$ moves toward zero, so does the within-group correlation, and the model reduces to the simple logit.
Defining the mean utility for product \( j \), \( \delta_{jt} = x_{jt}\beta + \xi_{jt} \), we are able to derive consumer \( i \)'s conditional indirect utility (1) as

\[
    u_{ijt} = \delta_{jt} + x_{jt}\Sigma v_{jt} + x_{jt}x_{jt}\Pi_{1j}D_{1jt} + x_{jt}x_{jt}\Pi_{2j}D_{2jt} + \xi_{igt} + (1-\rho)\epsilon_{ijt}
\]  

(2)

If \( \Sigma \) and \( \Pi \) are zero vector, we obtain the standard nested logit model. If \( \rho = 0 \), the withingroup correlation becomes zero, and consequently the model turns to be the BLP random coefficient logit model. If \( \Sigma, \Pi \) and \( \rho \) are all zero or zero vector, it will be a simple logit model.

Each consumer \( i \) in market \( t \) chooses the product \( j \) that maximizes her utility. The aggregate market share for product \( j \) in market \( t \) is the probability that product \( j \) yields the highest utility across all products (including the outside good 0). The predicted market share of product \( j = 1, ..., J \) in market \( t \), as a function of the mean utility vector \( \delta \) and the parameter vector \( \theta = (\beta, \sigma, \pi, \rho) \), is the integral of the nested logit expression over the standard normal random variable vector \( v \) and \( D \).

\[
    s_{jt}(\delta, \theta) = \int_{v, D} \frac{\exp \left( \frac{(\delta_{jt} + x_{jt}\Sigma v_{jt} + x_{jt}x_{jt}\Pi_{1j}D_{1jt} + x_{jt}x_{jt}\Pi_{2j}D_{2jt})/(1-\rho) \right)}{\exp(l_{jt}/(1-\rho))} \exp l_{jt} dP_{v}^{*}(v)dP_{D}^{*}(D)
\]  

(3)

where \( l_{jt} \) and \( I \) are McFadden's (1978) “inclusive values” defined by

\[
    l_{jt} = (1-\rho)ln \sum_{i=1}^{J} \exp((\delta_{jt} + x_{jt}\Sigma v_{jt} + x_{jt}x_{jt}\Pi_{1j}D_{1jt} + x_{jt}x_{jt}\Pi_{2j}D_{2jt})/(1-\rho)) \quad \text{and} \quad l_{i} = ln(1 + \sum_{g=1}^{G} \exp(l_{ig})).
\]

We approximate the integral over \( v \) and \( D \) by simulating that \( R \) draws over the density of \( v \) and \( D \);

\[
    s_{jt}(\delta, \theta) = \frac{1}{n_{v}} \sum_{i=1}^{n_{v}} \frac{\exp \left( \frac{(\delta_{jt} + x_{jt}\Sigma v_{jt} + x_{jt}x_{jt}\Pi_{1j}D_{1jt} + x_{jt}x_{jt}\Pi_{2j}D_{2jt})/(1-\rho) \right)}{\exp(l_{jt}/(1-\rho))} \exp l_{jt}
\]  

(4)

**Instruments**

In an effort to deal with endogeneity issues, we specify instruments for the demand equations. Prices are likely to be related with the unobserved characteristics of products, such as service, quality and brand (Nevo, 2001). To separate the endogenous variation, we use instruments that are related with prices and not related with product characteristics. We consider using the instruments used in previous research (Berry et al., 1995; Nevo, 2001). For product \( j \), we use prices and characteristics of other products in the market excluding product \( j \) as instrument variables. Those variables are not likely to be related with unobserved characteristics. However, they are likely to be associated with product \( j \)'s observed characteristics including price. Therefore, we consider instrument variables such as the average prices, the average discount rates, the average sale periods and the average validity terms of other products in the market besides product \( j \). These variables are expected to be associated not with unobserved characteristics but with prices.

**Estimation**

To estimate the demand parameters \( \theta \), we refer to Berry (1994), BLP and the subsequent literature. We equate the observed market share vector (i.e. unit sales per product divided by the number of potential consumers \( L \)) to the predicted market share vector, \( s_{t} = s_{t}(\delta, \theta) \). We solve this system for \( t \) in each market \( t \), using a slight modification of BLP's contraction mapping for the nested logit model, referencing...
Brenkers and Verboven (2006). Since the error term enters additively in \( \delta_t \), this gives a solution for the error term \( \epsilon_{ijt} \) for each product \( j \) in market \( t \). We then interact this with a set of instruments providing the instruments providing the moment conditions to proceed with GMM. We could estimate the parameters by minimizing the GMM object function.

**Results**

In order to check the robustness, we present three sets of results presented in Table 1 below: BLP, modified BLP and the RCNL. On top of the original BLP model, the modified BLP model reflects the pure characteristics proposed by Berry and Pakes (2007), representing consumers' different tastes toward individual product attributes without considering the tastes for certain products as a whole. According to Song (2011), product-level “taste shock” is related with the context of the market. The modified BLP model reflects the levels of consumer heterogeneity brought on by different product categories and characteristics. Meanwhile, we skip the application of the multiple choice model presented by Fan (2013), as consumers are not likely to make step-wise decisions in this setting where online daily deal sites send the information containing product price and characteristics via email and short messages.

Table 1. Results with BLP, modified BLP and RCNL

<table>
<thead>
<tr>
<th>Variable</th>
<th>BLP</th>
<th>Modified BLP</th>
<th>RCNL</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Sigma</td>
<td>Coefficient</td>
</tr>
<tr>
<td><strong>Discount Rate</strong></td>
<td>0.007***</td>
<td>0.009***</td>
<td>0.013***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td><strong>Discounted Price</strong></td>
<td>-0.014***</td>
<td>0.005***</td>
<td>-0.082***</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td><strong>Sale Period</strong></td>
<td>-0.341***</td>
<td>0.056***</td>
<td>-0.069***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.001)</td>
<td>(0.026)</td>
</tr>
<tr>
<td><strong>Term of Validity</strong></td>
<td>0.001**</td>
<td>0.000</td>
<td>0.002***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td><strong>Minimum Sale</strong></td>
<td>0.001***</td>
<td>0.001***</td>
<td>0.001***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td><strong>Maximum Sale</strong></td>
<td>0.000***</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td><strong>Threshold</strong></td>
<td>-1.665</td>
<td></td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(13.014)</td>
<td></td>
<td>(0.472)</td>
</tr>
<tr>
<td><strong>Sold-out</strong></td>
<td>0.891***</td>
<td>-0.283</td>
<td>-0.500</td>
</tr>
<tr>
<td></td>
<td>(0.214)</td>
<td>(0.472)</td>
<td>(0.485)</td>
</tr>
<tr>
<td><strong>Category Control</strong></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Region Control</strong></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>Week Control</strong></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td><strong>GMM-Obj.</strong></td>
<td>7.02E-05</td>
<td>4.33E-11</td>
<td>1.12E-09</td>
</tr>
</tbody>
</table>
To sum up the results of the structural models, most of the coefficients’ signals and significances are consistent across the models. We easily infer that the discount rate has a positive impact on voucher demand. Discounted price and sale period have a negative impact on voucher demand. Here, we have solid arguments for including excluded characteristics, as the coefficient for sale period increases as a result of our explicit treatment of product characteristics unobserved by the researcher but known to consumers in the market. In other words, deals with a long sale period are not as likely to attract consumers as are deals with a short sale period. Consumers may have more chances to purchase vouchers with a “short opportunity window” or as an impulse purchase, as a majority of deals end within 2 days. Terms of validity and minimum sale have a positive effect on voucher demand. The results for the dummy variables of threshold illustrate that reaching the threshold for the realization of the discount price is not a statistically significant factor on the demand.

According to the results from the RCNL model considering product and consumer characteristics, we estimate that, for a product with an average market share, a one per cent extension in the sale period is associated with a decrease in voucher demand by 0.22%. A one per cent extension in validity period is associated with an increase in demand by 0.16%. A one per cent increase in the price is associated with a decrease in demand by 2.43%, whereas one per cent increases in the number of discount rate, minimum sales and maximum sales are associated with increases in demand by 0.87%, 0.44% and 0.03%, respectively. Cross elasticity results show that a one per cent extension in the sales period of a competitive product with the same market share is associated with an increase in voucher demand by 0.001% on average, while a one per cent extension in the validity period of a competitive product with the same market share is associated with a decrease in demand by 0.001%. A one per cent increase in the price of the competitive product with market share is associated with an increase in demand by 0.012%, whereas one per cent increases in the number of discount rate, minimum sales and maximum sales of a competitive product with the same market share are associated with decreases in demand by 0.004%, 0.002% and 0.0002%, respectively. Furthermore, we investigate the single category samples in order to deal with the issues from the assumption of RCNL that each consumer only purchases one product out of the market. Using the samples of restaurant category, we find that the results confirm our findings with the multiple category samples.
One of most practical benefits of structural modeling is that it can provide counter-factual experiments to help in making decisions. We have presented some results which are of interest to merchants after conducting several counter-factual experiments. To identify the effects of the sales period, we assume a sale period of 1 to 5 days, as we know that more than 99 percent of deals are sold within a 5-day sale period. All else being equal, a one-day extension of sales will decrease the product's weekly market share by 8.9%. The results from the counter-factual experiments on the sales period are illustrated in Figure 1. Additionally, we assume discount rates of 50%, 60%, 70%, 80% and 90%, as we know that more than 97 percent of deals offer at least a 50% discount. Then, we examine subsequent demand changes in each case through the counter-factual experiments. An extra 10% discount for vouchers with average market share will result in additional demand of approximately 15.5%.

Conclusions and Discussions

In this paper, we estimate demand for online daily deal vouchers redeemable at various places in categories such as restaurants and bars, travel, exhibitions and beauty and spa. We use structural models to analyze the actual transactional data set of an online daily deal site, considering both the product characteristics and the heterogeneous consumer attributes. We estimate demand using BLP, modified BLP and RCNL models, to find the counter-intuitive results that a longer sales time is likely to decrease sales unlike the traditional marketplaces. All else being equal, a one-day extension of sales is estimated to decrease the product's weekly market share by 8.9%. We infer that attention economy exists in online daily deals from the viewpoint that limited time offers draw consumers' attention and consequently lead to additional sales. Our analysis provides a practical implication that the best strategy for revenue maximization inferred from our models is that merchants on daily deal sites would rather have high discount rates and short sales period if other things are equal.

Our work still has many areas which can be improved upon in future studies. We should extend to a more thorough analysis of the attention economy effects. The empirical analysis undertaken in this study is not able to establish a model that consumers narrow down their choices of online daily deals and then make a purchase decision from the funneled choices as we could not analyze user-level data sets. In spite of these limitations, as an empirical study using structural models to demand estimation in electronic marketplaces, our paper, we believe, can pave the way for future research in this exciting domain.

References


