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by Christian Rojas
and Everett B. Peterson

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Estimating Demand for Differentiated Products: The Case of Beer in the U.S.

Christian Rojas*

Everett B. Peterson

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*Rojas is Visiting Assistant Professor of Economics in the School of Social Sciences at the University of Texas at Dallas. Peterson is Associate Professor in the Department of Agricultural and Applied Economics at Virginia Tech.

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Abstract

This paper employs a nation-wide sample of supermarket scanner data to estimate a large brand-level demand system for beer in the U.S. Unlike previous studies, this work estimates the own- and cross-advertising elasticities in addition to price elasticities. The dimensionality problem is solved with the Distance Metric method of Pinkse, Slade and Brett and the demand model follows the flexible Almost Ideal demand system. While price elasticities are consistent with previous results, positive and negative cross-advertising elasticities imply the presence of both cooperative and predatory effects of advertising expenditures across brands; however, the former effect appears to dominate suggesting that advertising increases the overall demand for beer.

Keywords: Demand, differentiated products, distance metric, Almost Ideal Demand System, advertising, beer.

JEL Classification: D12, L66, M37

1 Introduction

Estimates of price demand elasticities are important inputs for the delineation of markets, measuring price competition and market power, and for predicting the competitive effects of mergers (Werden). While brand-level advertising elasticities are less commonly computed, they can be used to test whether advertising is predatory (it rearranges market shares) or cooperative (it shifts demand out) (Seldon and Doroodian; Slade, 1995). However, in the case of markets with many differentiated products, estimating brand-level own- and cross-elasticities is a difficult task due to the large number of unknown parameters to be estimated. This dimensionality problem coupled with data limitations has constrained previous applications to either focus only on pricing behavior or focus only on a few brands (or firms). In this paper we combine recent methods in demand estimation for differentiated products and a rich brand-level nation-wide data set to estimate both the price and advertising elasticity matrices at the brand level.

In addition to investigating the role of advertising, incorporating advertising into the demand system is particularly important for the validity of our instruments. Following the previous work of Hausman, Leonard and Zona, and Hausman, we employ the assumption that demand shocks are independent across regions and use prices in other regions as our price instruments. Unlike previous applications that employ this assumption, controlling for advertising reduces the likelihood of common demand shocks across regions thereby making our instruments more apt to be uncorrelated with the error term.

The dimensionality problem is commonly addressed by placing some restrictions on the cross-coefficients due to the limited number of observations available. Neoclassical demand models, such as those used by Hausman, Leonard and Zona, and Hausman rely on the assumption of weak separability to reduce the number of independent cross-price coefficients. The drawback with this 'multistage' approach is that the elasticity estimates are dependent on the assumed separable structure of the utility function, which is difficult to test empirically. In addition, consumer heterogeneity is difficult to incorporate into "representative consumer" neoclassical models.

An alternative to the neoclassical models is the aggregate version of the discrete choice (DC) demand model. Variants of the DC model are attractive because they explicitly model consumers' heterogeneity of preferences over product attributes, which may be the main reason why firms differentiate their products. Also, DC models reduce the number of coefficients by projecting the number of products on to a lower dimensional space, namely the product characteristics. The main drawbacks of DC models are the independence of irrelevant alternatives (IIA) property in logit and nested logit models and the computational complexity in the random coefficients model. Another potential drawback for DC models is that they are based on the assumption that the consumer purchases a single unit of the differentiated product. While this assumption is appropriate for products such as automobiles, it clearly does not fit consumer behavior in many differentiated product markets.

To overcome the dimensionality limitation of neoclassical demand models, Pinkse, Slade and Brett (PSB) developed a Distance Metric (DM) technique for the computation of the cross-price coefficients. The DM technique handles the dimensionality problem by specifying the cross-price terms as a function of each brand's location in product space relative to other brands. A brand's location in product space is determined from its observed product characteristics. Various distance measures between brands may be constructed from their relative location in product space and used as weights to create cross-price indices for each distance measure. The cross-price coefficients and elasticities can then be computed using the estimated coefficients for the cross-price indices and the distance measures between brands. The advantage of DM method is that it is easier to estimate than random coefficient DC models and allows testing the existence and strength of different product groupings as potential sources of competition, instead of ad-hoc segment definitions as in the multistage approach and nested logit models. Importantly, this technique accounts for the role that a brand's location in product space plays in differentiated products industries.

In this paper, we apply the DM method to both price and advertising. Furthermore, we use a more flexible underlying indirect utility function than previous applications (Pinkse and Slade; and Slade, 2004). In these two studies, the demand equations are derived from a quadratic indirect utility function and the resulting non-linear demand can only be linearized if the data consists of one or two cross-sections. Another drawback with the quadratic utility function is that it assumes that all consumers have the same constant marginal utility of income. To relax these limitations, we utilize the Almost Ideal Demand System (Deaton and Muellbauer) and its underlying indirect utility function.

The data set is comprised of brand-level prices and quantities collected by scanning devices in 58 major metropolitan areas of the United States over a period of 20 quarters (1988-1992). We match this data set with brand-level advertising expenditures and estimate a demand system for 64 brands of beer, produced by 13 different brewers. Advertising is incorporated because of the important role that advertising plays in this industry (e.g. Elzinga; Greer; Tremblay and Tremblay) and because of the increasing interest of researchers in non-price aspects of markets. This is the first study of the U.S. brewing industry at the brand level that incorporates brewers' advertising expenditures in its demand analysis, and perhaps the first study in any industry to compute a large number of cross-advertising elasticities.

While our estimated price elasticities are consistent with previous work, the estimated advertising elasticities convey new results. Positive and negative cross-advertising elasticities imply the presence of both cooperative and predatory effects of advertising expenditures across brands; however, the former effect appears to dominate suggesting that advertising increases the overall demand for beer. This is an important result in the long debate about the effects of advertising on alcohol consumption and lends support for the cooperative nature of advertising in this industry.

2 Empirical Model

While the DM method requires that the cross-price effects be functions of brands' relative locations in product space, it does not constrain the functional form utilized. In this paper, a linear approximation to the Almost Ideal Demand System (LALIDS), developed by Deaton and Muellbauer, is used because it allows a specification that is linear in the parameters to be estimated. Attempting to estimate an Almost Ideal Demand System that is non-linear in the parameters and incorporates the DM method is not practical given the large number of products. The ALIDS is defined as:

$$w_{jt} = a^{*}_{jt} + \sum_{k=1}^{n} b_{jk} \log p_{kt} + d_j \log(x_t / P_t) \quad (1)$$

The $t = \{1,\ldots,T\}$ subscript denotes the market, which is defined as a city-quarter pair in this study, $w_{jt} = p_{jt}q_{jt}/x_t$ is brand *j*'s sales share in market *t*, p_{jt} is the price of brand *j* in market *t*, q_{jt} is the quantity purchased of brand *j* in market *t*, $x_t = \sum_{j=1}^{n} p_{jt}q_{jt}$ is the level of total expenditures in market *t*, and P_t is the price index in market *t*. Following Moschini, a log-linear analogue of the Laspeyeres price index (P^L) is used instead of the Stone price index to linearize the ALIDS. This index is defined by:

$$\log P_t^L = \sum_{j=1}^{n} w_j^o \log(p_{jt}) \qquad (2)$$

where w_j^o is base share for brand *j*, which is defined as $w_j^o = T^{-1}\sum_{t=1}^{T} w_{jt}$.

Pinkse and Slade and Slade (2004), in contrast, derive a non-linear demand equation from a quadratic indirect utility function. In order to obtain a linear demand equation, they set the price index in the denominator to 1, losing (almost) no generality since their application is limited to a small time series. In contrast, the LALIDS specification places no restrictions on the number of cross-sections for estimation.

Following Sutton (45-46) advertising is assumed to be persuasive rather than informative. We focus on *traditional advertising* (e.g. television, radio and press), rather than on local promotional activity (e.g. local paper, in-store promotions, and end-of-aisle product location), as the key advertising variable because it has played a crucial role in the development and research of the industry. Also, traditional advertising is more apt to be independent of the pricing strategy, since, in general, mass media advertising by brewers seldom informs consumers about price. Further, only the flow effects of advertising are considered with all lagged own- and cross-advertising terms being omitted from the demand equation.[1]

Advertising is incorporated into equation (1) through the intercept term a_{jt}^*, which is modified to equal:

$$a_{jt}^* = a_{jt} + \sum_{k=1}^{n} c_{jk} A_{kt}^{\gamma} , \qquad (3)$$

where A_{kt} represents advertising expenditures of brand *k* in market *t*.[2] The parameter γ is included to account for decreasing returns to advertising. Following Gasmi, Laffont and Voung, γ is set equal to 0.5. The constant term a_{jt} incorporates time, city and brand binary variables as well as product characteristics and other market specific variables (e.g. demographics). Substituting equation (3) into equation (1) and adding an econometric term gives:

$$w_{jt} = a_{jt} + \sum_{k=1}^{n} b_{jk} \log p_{kt} + \sum_{k=1}^{n} c_{jk} A_{kt}^{\gamma} + d_j \log\left(x_t / P_t^L \right) + \varepsilon_{jt} . \tag{4}$$

Equation (4) can now be interpreted as a first-order approximation in prices and advertising to the demand function that allows for unrestricted price and advertising parameters. The usual practice with ALIDS is to estimate all coefficients by specifying (n – 1) *seemingly unrelated* equations, one for each product. However, with 64 brands this task becomes problematic given the large number of parameters to be estimated. The DM method, as explained in the next section, is utilized to reduce the dimensionality of the estimation.

The Distance Metric (DM) Method

The cross-price and cross-advertising coefficients (b_{jk} and c_{jk}) in equation (4) are specified as functions of different distance measures between brands *j* and *k*. These distance measures may be either continuous or discrete. For example, the alcohol content of a brand is an example of a variable that can be used to construct a continuous distance measure. Dichotomous variables that identify brands by product segment, such as light beer or premium beer, can be used to construct a discrete distance measure. The continuous distance measures use an inverse measure of Euclidean distance, or closeness, in product space between brands *j* and *k*.[3] This measure of closeness varies between zero and one, with a value of one if both brands are located at the same location in product space. The discrete distance measures take the value of 1 if *j* and *k* belong to the same grouping and zero otherwise.

Following Pinkse, Slade and Brett, we define the cross-price and cross-advertising coefficients to be equal to $b_{jk} = g(\delta_{jk})$ and $c_{jk} = h(\mu_{jk})$, where δ_{jk} and μ_{jk} are the set of distance measures for price and advertising, respectively.[4] Then, equation (4) can be written as:

$$w_{jt} = a_{jt} + b_{jj} \log p_{jt} + c_{jj} A_{jt}^{\gamma} + \sum_{k \neq j}^{n} g(\delta_{jk}) \log p_{kt} + \sum_{k \neq j}^{n} h(\mu_{jk}) A_{kt}^{\gamma} + d_j \log(x_t / P_t^L) + \varepsilon_{jt} . \tag{5}$$

The functions g and h measure how the strength of competition between brands varies with distance measures. These functions are specified as a linear combination of the distance measures:

$$g = \sum_{l=1}^{L} \lambda_l \delta_{jk}^l \text{ , and} \tag{6}$$

$$h = \sum_{m=1}^{M} \tau_m \mu_{jk}^m \tag{7}$$

where λ and τ are coefficients to be estimated, L and M are the number of distance measures for price and advertising, respectively. Because the distance measures are symmetric by definition ($\delta_{jk} = \delta_{kj}$ and $\mu_{jk} = \mu_{kj}$), symmetry may be imposed by setting λ and τ to be equal across equations. This implies that $b_{jk} = b_{kj}$ and $c_{jk} = c_{kj}$. The cross-price and cross-advertising coefficients (b_{jk}, c_{jk}) and elasticities are then recovered from the estimates of λ and τ, and the distance measures.

In principle, (n – 1) seemingly unrelated equations can be estimated. However, if n is very large, as is the case here with 64 brands, then it may become impractical to estimate such a large system of equations. One method to reduce the dimensionality of the estimation procedure is to assume that the own-price and own-advertising coefficients (b_{jj} and c_{jj}), as well as the coefficient on real expenditures (d_j), are constant across equations thereby reducing estimation to a single equation. Since this is too restrictive of an assumption, following Pinkse and Slade the coefficients b_{jj}, c_{jj}, and d_j are specified as functions of each brand's product characteristics. For example, using alcohol content as the only product characteristic, the own-price coefficient in equation (5) would be defined as $b_{jj} = b_1 + b_2 ALC_j$, where ALC_j is brand *j*'s alcohol content. Thus $b_{jj} \log p_{jt} = b_1 \log p_{jt} + b_2 \log p_{jt} ALC_j$, effectively interacting price with characteristics.

Combining equations (5), (6), and (7) with the own-price and own-advertising interactions described above yields:

$$\begin{aligned} w_{jt} &= a_{jt} + b_1 \log p_{jt} + \sum_{g=1}^{G} b_{g+1} \log p_{jt} PC_{gt}^{p} + c_1 A_{jt}^{\gamma} + \sum_{h=1}^{H} c_{h+1} A_{jt}^{\gamma} PC_{ht}^{A} + \\ &+ \sum_{k \neq j}^{n} \left(\sum_{l=1}^{L} \lambda_l \delta_{jk}^{l} \right) \log p_{kt} + \sum_{k \neq j}^{n} \left(\sum_{m=1}^{M} \tau_m \mu_{jk}^{m} \right) A_{kt}^{\gamma} + d_j \log(x_t / P_t^L) + \varepsilon_{jt} \end{aligned}$$

where PC_{gt}^{p} is the g^{th} characteristic of product *j* interacted with the own-price, and PC_{ht}^{A} is the h^{th} characteristic of product *j* interacted with own-advertising. After regrouping cross-prices into *L* weighted terms and cross-advertising into *M* weighted terms, the empirical model is written as:

$$\begin{aligned} w_{jt} &= a_{jt} + b_1 \log p_{jt} + \sum_{g=1}^{G} b_{g+1} \log p_{jt} PC_{gt}^{p} + c_1 A_{jt}^{\gamma} + \sum_{h=1}^{H} c_{h+1} A_{jt}^{\gamma} PC_{ht}^{A} + \\ &+ \sum_{l=1}^{L} \left(\lambda_l \sum_{k \neq j}^{n} \delta_{jk}^{l} \log p_{kt} \right) + \sum_{m=1}^{M} \left(\tau_m \sum_{k \neq j}^{n} \mu_{jk}^{m} A_{kt}^{\gamma} \right) + d_j \log(x_t / P_t^L) + \varepsilon_{jt} \end{aligned} \tag{8}$$

Note that the number of independent parameters for cross-price terms has been reduced from $n(n-1)/2$ to *L*. Similarly, the number of independent cross-advertising parameters has been reduced from $n(n-1)/2$ to *M*. In the analysis that follows, each cross-price and cross-advertising distance measure in each market is depicted as a (*n* x *n*) "weighing" matrix with element (*j*,*k*) equal to the distance between brands *j* and *k* when $j \neq k$, and zero otherwise. Thus, when the (*n* x *n*) weighing matrix is multiplied by the (*n* x 1) vector of brand prices or advertising in each market one obtains the appropriate sum over $k \neq j$ in the share equation.

Continuous Distance Measures

Three continuous product characteristics are utilized in this study: alcohol content (*ALC*), product coverage (*COV*), and container size (*SIZE*).[5] Product coverage measures the fraction of the market that is covered by a brand. Coverage for a brand in a given city is defined as the all commodity value (ACV) of stores carrying the product divided by the ACV of all stores in that city. Beers with low coverage may be interpreted as specialty brands that are targeted to a particular segment of the population. Beer is sold in a variety of sizes (e.g., six and twelve packs), and the variable *SIZE* measures the average package "size" of a brand. Higher volume brands (e.g., typical sales of twelve packs and cases) may compete less strongly with brands that are sold in smaller packages (e.g., six packs). The distance measures are computed in one-and two-dimensional Euclidean space and stored in "weighing" matrices (*W*) where the *j,k* entry in each matrix corresponds to the distance measure between brands *j* and *k*. The one-dimensional matrices are denoted *WALC*, *WCOV*, and *WSIZE* and the two-dimensional matrices are denoted *WAC*, *WAS*, and *WCS*, where *A*, *C*, and *S* stand for alcohol content, product coverage and container size, respectively.

Discrete Distance Measures

Three different types of discrete distance measures are utilized. The first type focuses on various product groupings including product segment, brewer identity, and national brand identity. Previous studies on beer have considered several different product segment classifications. With no clear consensus on product segment classifications we consider five different classifications: (1) budget, light, premium, super-premium, and imports, (2) light and regular, (3) budget, light, and premium, (4) domestic and import, and (5) budget, premium, super-premium, and imports.[6] The weighing matrices for the product segment classifications, denoted *WPROD1* through

WPROD5, are constructed such that element (j,k) is equal to one if brands j and k belong to the same product segment and zero otherwise.

A discrete distance measure for brewer identity is utilized to allow the model to determine if consumers are more apt to substitute between brands of the same firm when there are price changes, and if there are predatory, or cooperative, effects in advertising among beers produced by the same brewer. The weighting matrix *WBREW* is constructed such that element (j,k) is equal to one if brands j and k are produced by the same brewer and zero otherwise.

Because not all brands are sold in all city markets, the last product grouping classifies brands by whether they are regional or national brands. The distance measure constructed from this product grouping is used to test whether brands that are national (regional) compete more strongly with each other. The weighting matrix *WREG* takes a value of one if brands j and k are either both regional or both national, and zero otherwise. All weighing matrices constructed from product groupings are normalized so that the sum of each row is equal to one. This normalization allows the weighted prices and advertising expenditures of rival brands that are in the same grouping to equal their average.

Following PSB, two other types of discrete measures are constructed based on the nearest neighbor concept and if products share a common boundary in product space. Brands j and k share a common boundary if there is a set of consumers that would be indifferent between both brands and prefer these two brands over any other brand in product space (assuming consumers have a preferred bundle of product characteristics). The nearest neighbor (*NN*) and common boundary (*CB*) measures are computed for all brands based on their location in alcohol content and coverage space (weighing matrices *WNNAC* and *WCBAC*) and coverage and container size space (weighing matrices *WNNCS* and *WCBCS*). A j,k entry of a common boundary matrix is equal to one if brands *j* and *k* share a common boundary and zero otherwise while a *j,k* entry of a nearest neighbor matrix is equal to one if brands *j* and *k* are nearest neighbors (mutual or not) and zero otherwise.

Because the continuous product characteristics alcohol content (*ALC*), product coverage (*COV*), and container size (*SIZE*) have different units of measurement, their values are rescaled before computing the weighing matrices.[7] To restrict the product space for each of these characteristics to values between 0 and 1, each continuous product characteristic is divided by its maximum value. Restricting the product space in this manner eased the calculation of the common boundaries. Without this restriction, common boundaries of brands located on the periphery of the product space are difficult to define.

To illustrate the location of brands in product space and their common boundaries, figure 1 depicts the location of 41 brands in coverage and container size (*CS*) space in Chicago for the fourth quarter of 1992. There is a clustering of brands that are of medium size, around 0.5 or 12 packs, and that are carried by most of the stores (coverage between 0.8 and 0.9). These brands have a greater number of neighbors and hence face more local competition.

In addition to using product characteristics, a second set of nearest neighbor and common boundary measures are computed using product characteristics and price. Including price to calculate the nearest neighbor and common boundary measures allows consumers' brand choices to be influenced by both the distance in characteristics space and in price. For this case, nearest neighbors and common boundaries are identified based on the square of the Euclidean distance between brands plus a price differential between brands. The square of the Euclidean distance is employed because a common boundary is defined by a non-linear equation when price is added to Euclidean distance, increasing computational time and complexity.

Own-Price and Own-Advertising Interactions

Two product characteristics are interacted with own-price and own-advertising in the model: the inverse of product coverage (1/*COV*) and the number of common boundary neighbors (*NCB*). The number of common boundary neighbors is a measure of local competition that determines the number of competitors that are closely located to a brand in product space. *NCB* is computed in product coverage-container size space and alcohol content-coverage space.

3 Data

Table 1 provides a description and summary statistics for all variables used in this study. The main data source is the Information Resources Inc. (IRI) Infoscan Database.[8] The IRI data includes prices and total sales for several hundred brands for up to 58 cities over 20 quarters (1988-1992). Volume sales in each city are reported as the number of 288-ounce units sold each quarter by all supermarkets in that city area and price is an average price for a volume of 288 oz for each brand. To maintain focus on brands with significant market share, all brands with a local market share of less than 3% are excluded from the sample. Using this selection criterion, 64 different brands produced by 13 different brewers are included in the sample. On average there are 37 brands sold in each city market with a minimum of 24 brands and a maximum of 48 brands. Appendix A contains a table of all the brands chosen, their brewers and other details of the database and the data selection procedure.

In addition to price and sales data, the IRI database contains information on several additional brand specific and market variables. The variable *UNITS* provides the number of units, regardless of size, sold each quarter. These data are used to create an average size variable defined as $SIZE = Q\,/\,Units$, where *Q* is the total quantity sold measured in units of 288 ounces. The variable *COV* (Coverage) measures the market coverage for each brand and is defined as the sum of all commodity value (ACV) sold by stores carrying the product divided by the ACV of all stores in the city. Lastly, the variable OVER50K, which is the fraction of households that have an income above $50,000 in each city-quarter pair, was also included in the estimation.

Advertising data (A) was obtained from the Leading National Advertising annual publication. These are quarterly data by brand comprising total national advertising expenditures for 10 media types. Alcohol content (ALC) was collected from various specialized sources. It is assumed that alcohol content remains constant for each brand.[9] The binary variable (REG) takes a value of one if brand j is a regional brand and zero if it is a national brand.

4 Estimating the Demand Model

Given the strategic nature of price and advertising, all terms in equation (8) that contain these two variables are treated as endogenous and thus correlated with the unobserved demand shock. To avoid simultaneity bias, an instrumental variables approach is used to consistently estimate the model parameters.

Let n_z be the number of instruments, Z the $(T \times n) \times n_z$ matrix of instruments, S the collection of right hand side variables in equation (8) and θ the vector of parameters to be estimated. The generalized method of moments (GMM) estimator is used:

$$\hat{\theta}_{GMM} = (S'P_z S)^{-1} S'P_z \underline{w},$$

with consistent estimator for its asymptotic variance:

$$A\,\mathrm{var}(\hat{\theta}_{GMM}) = (S'P_z S)^{-1},$$

where, $P_z = Z(Z'\hat{\Omega}Z')^{-1}Z$, and $\hat{\Omega}$ is a $(T \times n) \times (T \times n)$ diagonal matrix, with diagonal element $\hat{\varepsilon}_j^2$ equal to the squared residual obtained from a ‘first step’ *2-stage least squares* regression.[10]

Instruments

As in previous work, the instruments employed in this paper rely on the identification assumption that, after controlling for brand, city, and time specific effects, demand shocks are independent across cities. Because beer is produced in large-scale plants and then distributed to various states, prices of a brand across different markets share a common marginal cost component, implying that prices of a given brand are correlated across markets. If the identifying assumption is true, prices will not be correlated with demand shocks in other markets and can hence be used as instruments for other markets. In particular, the average price of a brand in other cities is used as its instrument.

The data employed in this study is based on broadly defined city/regional markets. These broad market definitions, which are similar to those used by the Bureau of Labor Statistics, reduce the possibility of potential correlation between the unobserved shocks that affect two markets. By including national advertising expenditures in the demand equation, we are attempting to control for advertising related demand shocks that may be correlated across markets. In general, any unobserved regional or national shock, like an interest rate shock will affect demand in various markets and will violate the independence assumption. To further control for such unobserved national shocks, time dummies are included in the specification.

Although a similar instrument could be constructed for advertising, brand-level advertising expenditures are only observed at the national level in each quarter and are thus invariant across markets. Alternatively, lagged advertising expenditures are used as instruments for advertising. This can be done if the identifying assumption is extended to independence of demand shocks over time, in addition to across cities, and there is correlation of advertising expenditures over time. Since expenditures, (x_t), are constructed with price and quantity variables, this term is also treated as endogenous and instrumented with median income (*INC*). A final identification assumption, which is common practice in the literature, is that product characteristics are assumed to be mean independent of the error term.

Whereas the identifying assumption of independence of demand shocks across markets may be problematic and difficult to assess, it has been widely used in the literature: Hausman, Leonard and Zona, Slade (1995), Hausman, Nevo (2000, 2001), Pinkse and Slade, and Slade (2004). Nevo assumes independence of the demand shock over markets and over time, as is assumed here. Despite its wide acceptance, the validity of the proposed instruments is assessed by conducting a formal test. Following Nevo (2001), additional instruments for price are created as proxies for city-specific marginal costs and an overidentifying restrictions test is performed. The proxies utilized are city density (*DEN*) for the cost of shelf space and average wage in the retail sector (*WAGE*) for supermarket labor costs (see Appendix A for details).

As observed by Berry (1994), an additional source of endogeneity may be present in differentiated products industries. Unobserved product characteristics (included in the error term), which can be interpreted as product quality, style, durability, status, or brand valuation, may be correlated with price and produce a bias in the estimated price coefficient. Following Nevo (2001), this source of endogeneity is controlled for by exploiting the panel structure of the data with the inclusion of brand-specific fixed effects. These fixed effects control for the unobserved product characteristics that are invariant across markets, reducing the bias and improving the fit of the model. While brand fixed effects do not control for unobserved product characteristics that are city specific, the instruments discussed at the beginning of this section address this issue.

One final detail on demand estimation is that the inclusion of brand fixed effects capture market-invariant product characteristics and hence their coefficients can not be identified directly.

These coefficients are recovered using a minimum distance procedure, as suggested by Nevo (2000, 2001). The estimated coefficients on the brand dummies from the demand equation (in which the market-invariant characteristics and the constant are omitted) are used as the dependent variable in a GLS regression, while the market-invariant product characteristics and a constant are used as the explanatory variables.

5 Results

Given the large number of possible distance measures and high levels of collinearity between these measures, several preliminary OLS regressions are used to determine the most relevant continuous and discrete product spaces for cross-price and cross-advertising terms. Each OLS regression is a restricted version of equation (8) in which either one cross-price term or one cross-advertising term is specified. Table 2 reports the estimated coefficients and *t-statistics* on the weighted cross-term using each of the distance measures. Each of these coefficients was estimated in a separate OLS regression.

First, one- and two-dimensional continuous distance measures constructed from alcohol content, product coverage, and container size were used to weigh rival prices and rival advertising. Results for the one-dimensional distance measures indicate that cross-price coefficients appear to depend on closeness in alcohol content and product coverage. The cross-advertising coefficients depend on closeness in product coverage and container size. Results for the two-dimensional distance measures indicate that closeness in alcohol content-product coverage and product coverage-container size space is important for both rival prices and advertising. Because using the same product space for both rival prices and advertising causes the weighted rival prices and advertising to be highly collinear when pooled in one regression, alcohol content-product coverage is assumed to be the relevant product space for weighing rival prices and product coverage-container size is assumed to be the relevant product space for advertising.

Using these relevant continuous product spaces, we next consider similar OLS regressions with common boundary and nearest neighbor distance measures. For rival prices, the common boundary measure that includes price and the nearest neighbor measure without price perform better than their counterparts. For rival advertising, the distinction between including or not including price in common boundary and nearest neighbor distance measures is not clear. The *t*-statistics for the measures without price are slightly larger than their counterparts.

The last set of regressions focus on discrete measures constructed from product groupings. The positive coefficient on rival prices weighted by brewer identity indicates that consumers are more apt to substitute between brands of the same firm. This notion of substitution among a brewer's brands is reinforced by the negative coefficient on this measure for rival advertising which indicates that advertising of a particular brand leads to a reduction in the sales of other brands produced by the brewer. The positive coefficient on rival prices weighted by *WREG* indicates that national brands are closer rivals to each other than to regional brands and vice versa; however, the positive coefficient on rival advertising weighted by *WREG* suggests the existence of cooperative effects of advertising among regional brands as well as among national beers.

For weighted rival prices, coefficients using different product segments take positive and negative values. Since brands that belong to the same product segment should be substitutes, the negative coefficients for product segments 4 and 5 have the wrong sign and indicate these product classifications are not appropriate. The only positive coefficient that is significant for rival prices is that of product classification 2 (W*PROD2*). This indicates that cross-price effects are larger for same-segment beers (either light or regular). For rival advertising, on the other hand, the coefficients on all product segments are negative. The largest and most significant coefficient is that of product classification 3 (W*PROD3*). This classification is similar to 2 except that it includes the “budget” category in addition to light and regular.

Brand Share Equation

Because of the endogeneity of price and advertising, the brand share equation is estimated using a GMM estimator. Results from OLS regressions were used to guide the choice of variables in the final specification. However, not all variables were significant while others produced collinearities when pooled in a single regression. For example, there was a high-level of collinearity between the cross-prices weighted by the alcohol content-product coverage (*WAC*) distance measure and cross-advertising expenditures weighted by the product coverage-container size (*WCS*) distance measure. Weighting cross-advertising expenditures by container size only (*WSIZE*) reduced the collinearity problem while not affecting the other parameter estimates. In addition, to allow for variation by brand of the own-price and own-advertising terms, we tried different interactions of price (and advertising) with different product characteristics and included those that were significant in the final specification.

Table 3 reports the GMM regression results for two different models. The difference between models 1 and 2 is the inclusion of brand dummies. The two models contain time and city/market binary variables (estimated coefficients not reported in table 3). Because alcohol content, brewer dummies and product segment variables for a brand are constant across time and city, their coefficients can not be directly identified when brand dummies are included in model 2. A minimum distance (MD) procedure is utilized to recover these coefficients (see section 4). A second-stage regression is performed with the estimated coefficients on brand dummies as the dependent variable and alcohol content (*ALC*), product segments (budget, light, premium, super-premium and import), brewer dummies, and a constant as explanatory variables.

The estimated coefficients from the MD procedure for model 2 are reported in table 3. While the market-invariant product characteristics in the MD procedure explained only 12% of the variation in the coefficients of the brand dummies, all coefficients recovered from the MD procedure except for the constant are significantly different from zero at the 1% level. The positive coefficients on the product segment binary variables indicate that these product segments have larger budget shares than the light (or base) product segment. An increase in alcohol content is associated with a larger budget share.

The only product-specific variable that does vary by market is the number of common boundaries in alcohol content-product coverage space (*NCBAC*). The negative coefficient on *NCBAC* shows that brands that share a common boundary with more neighbors in alcohol content - coverage space have a lower sales share than those with fewer common boundaries. Thus, the higher number of close neighbors, the greater the competition between brands. Conversely, the demographic variable *OVER50K* has a negative sign which implies that sales tend to be smaller in cities where the fraction of high income families is larger. This finding is consistent with the fact that more that half of beer is consumed by households with an annual income of $45,000 or less (Beer Institute).

The estimated coefficients for own-price, own-advertising, and their interactions with product characteristics are reported in the second group in table 3. Because price and advertising are highly correlated with their corresponding interactions with product coverage, the inverse of this latter variable (1/*COV*) is used to avoid collinearity. The own-price and own-advertising coefficients are significantly different from zero at the 1% level and have the expected negative and positive signs. The negative coefficients on the interaction of price and advertising with the inverse of product coverage indicates that as the coverage of a brand increases, the own-price effect for that brand decreases (becomes less negative) while the own-advertising effect increases (becomes more positive). Thus, the sales of brands that are widely sold within a city are less sensitive to a change in price than are brands that are less widely available. Also, advertising is more effective for brands that are more widely sold. Finally, as the number of common boundaries increases the own-price effect increases (becomes more negative) and the own-advertising effect decreases. This shows that higher brand competition is associated with more price responsive demand and less effective advertising.

Comparing models 1 and 2, the estimated own-price coefficient is nearly twice as large in absolute terms when brand dummies are included. Conversely, the own-advertising coefficient decreased by approximately 80 percent in model 2 compared to model 1. The better goodness-of-fit of model 2 and the magnitude of change on both price and advertising coefficients highlight the importance of accounting for endogeneity (resulting from unobserved product characteristics) with the inclusion of brand dummies. Furthermore, the overidentification test in model 2 (p-value=0.50) suggests that the choice of instruments is valid. Discussion of results is henceforth based on the GMM version of model 2.

In model 2, the estimated coefficients on the weighted cross-price terms are all positive. Thus, brands that are closer in the alcohol content-product coverage space (both in terms of Euclidean distance and nearest neighbor), produced by the same brewer, have similar geographic coverage, or belong to the same product segment are stronger substitutes than other brands. Intuitively, consumers will more likely switch to a brand located nearby in product space and/or produced by the same brewer than to more distant brands. Based on the magnitude of the estimated coefficients, the strongest substitution effects are for brands in the same product segment and with similar geographic coverage.

With the exception of product segment, the estimated coefficients on weighted cross-advertising terms are positive. This suggests that there are cooperative effects in advertising across brands that are located more closely in the product space and with the same geographic coverage. However, the negative coefficient for product segment indicates that there are predatory cross-advertising effects for brands in the same product segment, thereby potentially offsetting some of the cooperative effects. In general, positive and negative cross-advertising effects have the same order of magnitude. As shown in table 5, there are more positive cross-advertising elasticities than negative cross-advertising elasticities, indicating that cooperative effects dominate predatory effects.

The estimated coefficient on real expenditures, $\log(x_t / P_t^L)$, is not statistically different from zero. Various specifications were tried that interacted product or market characteristics with real expenditures, but none of these specifications yields statistically significant coefficients. This result implies that the brand-level income elasticities are all equal to one.

Elasticities

Price and advertising elasticities are calculated for each city-quarter pair using the estimated coefficients from the GMM estimation of model 2 in table 3. The median own-price elasticity across all brands is -3.34 while the median own-advertising elasticity is 0.024. All own-price elasticities are negative while approximately 85% of own-advertising elasticities are positive. All cross-price elasticities are positive and have a median value of 0.0593 whereas cross-advertising elasticities have a median of 0.021. In general, median own-price elasticities are similar to those reported in Hausman, Leonard and Zona (-4.98), and Slade (-4.1). Cross-price elasticities are similar to those in Slade but an order of magnitude smaller than those reported by Hausman, Leonard and Zona.

Tables 4 and 5 contain a sample of the median values of the price and advertising elasticities for selected brands. To facilitate comparison of the cross-price and cross-advertising patterns, these tables also contain information on the distance measures used to compute the elasticities. Table 4 divides brands into light and regular. Brands that are located closer in product space have, in general, higher cross-elasticities. For example, Budweiser, Michelob, Coors, Miller Genuine Draft, and Miller High Life are located close to one another in the product space. The cross-price elasticities between these brands are generally larger than the cross-price elasticities with Keystone, Old Style, Olympia, Pabst, and all light beers. Estimated confidence intervals (not shown in table 4) indicate that all price elasticities are significantly different than zero at the 5% level.[11]

As shown in table 5, the median advertising elasticities vary considerably across brands. While all of the own-advertising elasticities in the table and most of the cross-advertising elasticities are positive, there are several negative cross-advertising elasticities. These negative cross-advertising elasticities occur between brands in the same product segment. This is due to the negative coefficient on the cross-advertising term that is weighted by product segment (table 3). In these cases, the predatory cross-advertising effects for brands in the same product segment outweigh the positive advertising cooperative effects from closely located brands. Not all of the advertising elasticity estimates are statistically different than zero, however. Approximately 85% of negative advertising elasticities and 86% of positive elasticities are significant at the 5% level (for both own- and cross-advertising elasticities).

Semi-parametric Results

As shown by Pinkse, Slade and Brett, parametric results may not always be consistent. They proposed a consistent semi-parametric estimator for the cross-price and cross-advertising weighing functions *g* and *h* that specifies one series expansion of the continuous distance measure for each discrete measure. Several alternative semi-parametric specifications were estimated as a means of providing some evidence that our parametric specification is not a restrictive version of the functions *g* and *h*. Each of the semi-parametric regressions contains either cross-price terms or cross-advertising terms, but not both due to collinearity problems, and all other variables in table 3. In each specification, only one of the discrete measures that enter the cross-terms in table 3 (e.g. *BREW* for cross-price) and a polynomial series expansion of order 4 is specified for the corresponding continuous measure (i.e. Alcohol-Coverage for price and Size for advertising). The results show that the value of the *g* function decays rapidly with Euclidean distance, suggesting that competition among beers is mainly local. This rapid decay of the value of *g* gives us some confidence about the consistency of the parametric specification (see Pinkse, Slade and Brett). For the function *h*, the expansion terms were rarely significant suggesting that non-linear terms are not important and hence the parametric specification is not a restrictive version of *h*.

6. Summary and Discussion

In this paper, we employ the Distance Metric method proposed by Pinkse, Slade and Brett to allow for estimation of cross-advertising elasticities in addition to cross-price elasticities. We also employ a flexible functional form that allows for estimation with panel data. We estimate a brand-level demand system for 64 brands of beer, produced by 13 different brewers, sold in the United States. The U.S. brewing industry is chosen because of the interest it has generated from researchers in the past and the important role that traditional advertising (television, radio, and press) plays in this industry (Elzinga; Greer; Tremblay and Tremblay) and other markets.

Much of the previous research on U.S. brewing has utilized aggregated industry data. Analysis of inter-brand competition can shed new light to earlier firm-level studies. For example, earlier work in the U.S. brewing industry addressed several aspects of rivalistic behavior in advertising with firm level data with the results being generally mixed (Nelson, 2005: 281-288). Our results suggest that advertising is important at the brand level and that for the most part it is cooperative. However, the existence of some negative cross-advertising elasticities indicates that predatory advertising does occur. In particular, light and regular beers (and to a lesser extent popular beers) appear to compete more aggressively with same-segment beers.

The generally cooperative nature of traditional advertising suggests that its use stimulates the overall demand for beer. This is contrary to an extensive literature that supports the view that advertising does not stimulate the demand for beer (Nelson, 1999; Nelson and Moran; Lee and Tremblay, and references cited therein). This argument was used by the Federal Trade Commission in a case that dealt with a petition from the Center for Science in the Public Interest (CSPI) in 1983 to ban broadcast advertising of alcohol (including beer). The FTC dismissed the petition on the grounds that advertising does not increase the consumption of alcoholic beverages.

The results in this paper may also be utilized to test alternative hypotheses of brand pricing behavior and market power. The rising concentration in the U.S. brewing industry, where the sales of the top three brewers account for more than 90% of domestic consumption, and the emergence of Anheuser-Busch as the sole industry leader raise concerns about deviations from competitive behavior (Tremblay and Tremblay: 283). Also, policy issues that relate alcohol consumption with health and taxes can be analyzed in more detail with brand level estimates.

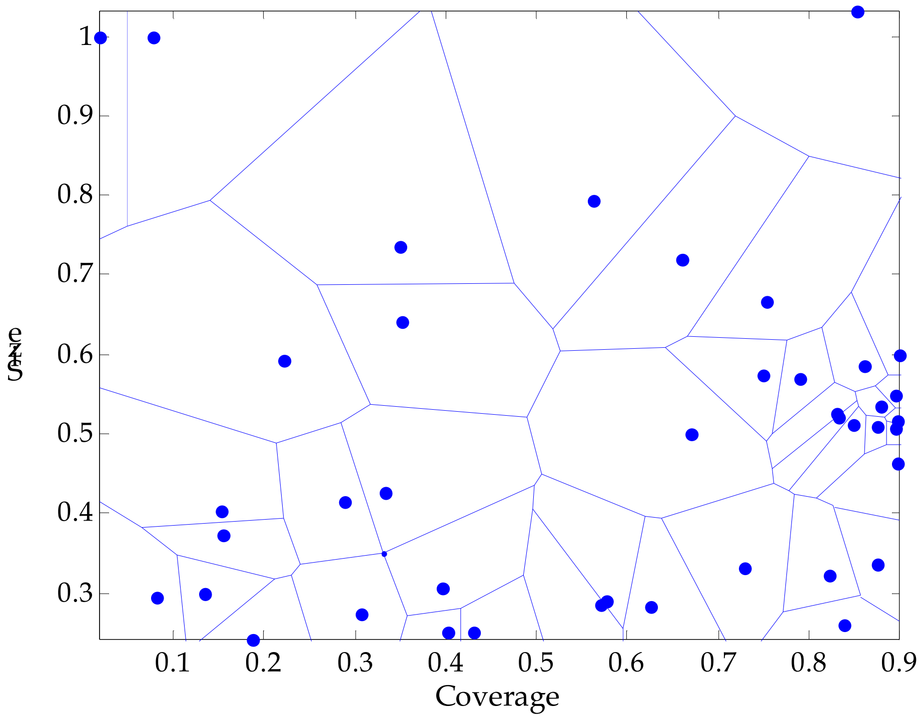

Figure 1: Location and Common Boundaries of Brands in Product Coverage - Container Size Space (Chicago, 4th Quarter-1992)

Table 1: Description and Summary of Statistics of Variables

Variable	Description	Units	Mean	St dev	Min	Max
	IRI Database					
Price	Average (per brand) Price	$/288oz	12.1	3.87	0.82	28.9
Quantity	Volume Sold	288 oz	23.5	63.6	0.00	2652
UNITS	Number of units sold, regardless of size	(000)	57.8	149.9	28.1	6111
COV	Sum of all commodity value (ACV) sold by stores carrying the product/ACV of all stores in the city	%	74.0	28.61	0.26	100
OVER50K	% of Households with income over $50,000/year	%	23.3	6.1	10.3	44.8
INC	Median Income	(000) of $	32.0	6.9	18.1	53.4
	Other Variables					
A	Quarterly national advertising	Mill of $	3.54	6.3	0	40.3
SIZE	Quantity/UNITS	N/A	0.38	0.117	0.07	1.30
ALC	Alcohol Content	% / vol	4.48	0.94	0.4	5.25
REG	1 if brand is regional, 0 otherwise	0 / 1	0.15	-	-	-
Budget	1 if brand is budget, 0 otherwise	0 / 1	0.37	-	-	-
Light	1 if brand is light, 0 otherwise	0 / 1	0.235	-	-	-
Premium	1 if brand is premium, 0 otherwise	0 / 1	0.185	-	-	-
Spremium	1 if brand is super-premium, 0 otherwise	0 / 1	0.10	-	-	-
Import	1 if brand is import, 0 otherwise	0 / 1	0.10	-	-	-
WAGES	Average wage of worker in retail sector	$/hour	7.3	1.17	3.58	12.3
DEN	Population per square mile	(000)	4.73	4.13	0.73	23.7

Source: IRI database, University of Connecticut; Bureau of Labor Statistics; Demographia; other sources.

Table 2. Estimated Coefficient on Weighted Prices and Weighted Advertising from separate OLS Regressions [a]

Distance Measure (Weighing Matrix Acronym)	Rival Price[b]		Rival Advertising	
Continuous Distance Measures	Coefficient	*t-stat*	Coefficient	*t-stat*
One-Dimensional				
Alcohol content (W*ALC*)	1.42**	*2.39*	0.02	*0.44*
Product coverage (W*COV*)	7.65*	*41.02*	0.43*	*57.56*
Container size (W*SIZE*)	0.23	*0.74*	0.21*	*11.37*
Two-Dimensional				
Alcohol content – product coverage (W*AC*)	10.84*	*27.30*	0.78*	*43.22*
Alcohol content – container size (W*AS*)	1.28**	*2.42*	0.17*	*4.93*
Product coverage – container size (W*CS*)	8.28*	*30.51*	0.58*	*49.79*
Discrete Distance Measures				
Common Boundary (CB)				
Alcohol content – product coverage (W*CB*AC)	0.83**	*2.08*		
Alcohol content – product coverage - price (W*CB*ACP)	5.20*	*12.10*		
Product coverage – container size (W*CB*CS)			0.38*	*32.70*
Product coverage – container size - price (W*CB*CSP)			0.53*	*25.05*
Nearest Neighbor (NN)				
Alcohol content – product coverage (W*NN*AC)	11.19*	*20.68*		
Alcohol content – product coverage - price (W*NN*ACP)	2.60*	*4.73*		
Product coverage – container size (W*NN*CS)			0.50*	*25.21*
Product coverage – container size - price (W*NN*CSP)			0.39*	*14.77*
Product Groupings				
National Identity (W*REG*)	62.59*	*4.49*	0.92***	*1.70*
Brewer Identity (W*BREW*)	29.28*	*6.41*	-0.29**	*-2.12*
Product classification 1[c] (W*PROD1*)	-2.07	*-0.17*	-1.08*	*-7.84*
Product classification 2 (W*PROD2*)	116.70*	*7.51*	-1.89*	*-7.46*
Product classification 3 (W*PROD3*)	19.36	*0.56*	-2.88*	*-13.66*
Product classification 4 (W*PROD4*)	-82.75*	*-4.87*	-2.03*	*-4.42*
Product classification 5 (W*PROD5*)	-42.85**	*-2.35*	-0.31**	*-1.96*

[a] Each coefficient (and its t-statistic) is obtained from a separate OLS regression in which the coefficient displayed in each cell above corresponds to the only weighted rival term included (i.e. either weighted rival price or weighted rival advertising). All regressions include city, brand, and time binary variables.

[b] Coefficients have been multiplied by 10,000 for readability.

[c] Product classifications are: (1) budget, light, premium, super-premium, and imports; (2) light and regular; (3) budget, light, and premium; (4) domestic and import; and (5) budget, premium, super-premium, and imports.

* Significant at 1%, ** significant at 5%, *** significant at 10%.

Table 3: Results of GMM Estimation of Demand Model

DEPENDENT VARIABLE: SALES SHARE (w_{jt})	Model 1		Model 2	
Variable; Description	Coeff.	(t-stat)*	Coeff.	(t-stat)*
Constant a_{jt}				
Brand Dummies	*no*	*no*	*yes*	*yes*
Constant**			-15.51	(-0.96)
ALC**			5.95	(3.24)
POPULAR**			49.98	(14.84)
PREMIUM**			63.52	(13.95)
SPREMIUM**			131.81	(23.85)
IMPORT**			211.18	(22.55)
NCBAC= # common boundary neighbors, Alcohol content - Coverage space	-1.15	(-0.85)	-3.91	(-3.66)
OVER50K	-94.84	(-0.57)	-240.0	(-1.90)
Own Price (*b*) and Own-Advertising (*c*)				
logP	-122.40	(-9.82)	-252.90	(-5.71)
logP $\times$ (1/COV)	-0.56	(-2.38)	-1.09	(-3.46)
logP $\times$ NCBCSP; NCBCSP= # common boundary neighbors CS – price space	-4.82	(-7.28)	-7.14	(-11.35)
A^{γ}	8.48	(31.15)	1.32	(4.39)
A^{γ} $\times$ (1/COV)	-0.68	(-5.58)	-0.19	(-3.47)
A^{γ} $\times$ **NCBCS**; NCBCS= # common boundary neighbors, CS space	-1.65	(-3.57)	-0.16	(-4.53)
Weighted Cross Price and Weighted Cross-Advertising Terms (λ_l and τ_m)				
*Distance Measures for **Price** (Weighing Matrix acronym)*				
Alcohol Content – Product Coverage, two-dimensional product space, (*WAC*)	2.10	(13.66)	5.32	(11.00)
Nearest neighbors in Alcohol Content – Product Coverage space (*WNNAC*)	-0.21	(-0.30)	8.87	(15.62)
Brewer identity (*WBREW*)	-12.18	(-5.38)	17.30	(5.31)
Product classification 2: Regular – light (*WPROD2*)	52.39	(6.62)	93.56	(3.99)
National Identity (*WREG*)	40.83	(5.85)	49.61	(5.39)
*Distance Measures for **Advertising** (Weighing Matrix acronym)*				
Container Size, one-dimensional product space (*WSIZE*)	0.17	(7.83)	0.16	(8.64)
Common boundary in product coverage – container size – price space (*WCBCSP*)	0.85	(15.50)	0.71	(15.23)
Nearest neighbors in product coverage – container size space (*WNNCS*)	0.61	(14.70)	0.40	(12.24)
Product Classification 3: Budget, light, and premium (*WPROD3*)	-2.78	(-14.58)	-3.22	(-9.10)
National Identity (*WREG*)	-3.02	(-21.79)	5.30	(2.65)
Price Index (*d*)				
$\log(x_t / P_t^L)$	28.15	(1.08)	27.35	(1.38)
R^2 (centered, uncentered)	0.40 , 0.58		0.66, 0.76	
J-Statistic (p-value)	0.90		0.50	
R^2 from MD regression			0.120	

* Asymptotic t-stats in parenthesis.

** Estimates from minimum distance (MD) procedure. The MD regression includes brewer dummies (not reported).

Based on 33,892 observations. Coefficients in table are original coefficients x 10^4. All specifications include, time and city dummies (not reported).

Table 4: Median Price Elasticities

Brewer	Beer	Bud	Michb	Coors	Kstone	Old Style	Olymp	Pabst	MGD	High Life	Bud Light	Busch Light	Michb Light	Coors Light	Kstone Light	Old St Light	MGD Light	Miller Lite
	Alcohol (ALC)	*4.9*	*5*	*5*	*4.8*	*5*	*4.8*	*5*	*5*	*5*	*4.2*	*4.2*	*4.3*	*4.2*	*4.2*	*4.1*	*4.5*	*4.5*
	Coverage (COV)	*0.96*	*0.94*	*0.93*	*0.72*	*0.54*	*0.59*	*0.72*	*0.95*	*0.95*	*0.95*	*0.82*	*0.92*	*0.95*	*0.76*	*0.52*	*0.87*	*0.95*
Anheuser-Busch	BUDWEISER	-1.152	0.006	0.005	0.005	0.004	0.005	0.005	0.005	0.005	0.004	0.004	0.004	0.003	0.003	0.002	0.003	0.003
	MICHELOB	0.060	-2.500	0.069	0.047	0.032	0.044	0.051	0.081	0.088	0.040	0.042	0.041	0.026	0.028	0.015	0.035	0.029
Adolph Coors	COORS	0.040	0.054	-2.263	0.070	0.036	0.036	0.042	0.063	0.068	0.023	0.031	0.023	0.050	0.053	0.017	0.035	0.026
	KEYSTONE	0.160	0.148	0.237	-6.072	0.125	0.186	0.149	0.147	0.149	0.095	0.097	0.099	0.183	0.181	0.065	0.107	0.108
Bond	OLD STYLE	0.275	0.288	0.277	0.336	-15.15	0.318	0.320	0.297	0.291	0.146	0.176	0.153	0.136	0.164	0.377	0.162	0.166
Pabst	OLYMPIA	0.104	0.098	0.096	0.139	0.103	-4.924	0.185	0.097	0.098	0.066	0.068	0.069	0.064	0.065	0.064	0.064	0.073
	PABST	0.083	0.097	0.100	0.078	0.037	0.155	-3.886	0.100	0.111	0.049	0.048	0.051	0.050	0.048	0.016	0.047	0.054
Philip Morris/Miller	MGD	0.026	0.034	0.037	0.023	0.019	0.020	0.028	-1.818	0.059	0.014	0.015	0.015	0.014	0.014	0.009	0.024	0.028
	HIGH LIFE	0.026	0.039	0.043	0.025	0.017	0.023	0.028	0.065	-1.831	0.015	0.015	0.015	0.015	0.015	0.007	0.032	0.030
Anheuser-Busch	BUD LT	0.010	0.010	0.006	0.006	0.003	0.006	0.006	0.006	0.006	-1.347	0.028	0.031	0.039	0.028	0.017	0.021	0.027
	BUSCH LT	0.031	0.030	0.021	0.023	0.010	0.020	0.021	0.021	0.021	0.105	-2.226	0.090	0.107	0.103	0.053	0.068	0.077
	MICHB LT	0.047	0.046	0.031	0.032	0.016	0.039	0.029	0.030	0.030	0.177	0.125	-2.622	0.165	0.125	0.096	0.137	0.132
Adolph Coors	COORS LT	0.007	0.007	0.014	0.012	0.005	0.006	0.007	0.007	0.007	0.040	0.030	0.031	-1.363	0.035	0.031	0.024	0.028
	KEYST LT	0.056	0.054	0.109	0.113	0.031	0.053	0.053	0.054	0.054	0.236	0.246	0.211	0.334	-4.112	0.137	0.167	0.198
Bond	O.STYLE LT	0.169	0.162	0.162	0.197	0.933	0.192	0.161	0.162	0.162	0.915	0.869	0.917	0.926	1.128	-16.966	0.576	0.886
Philip Morris/Miller	MGD LT	0.021	0.020	0.020	0.022	0.013	0.021	0.020	0.035	0.035	0.064	0.068	0.065	0.064	0.064	0.054	-2.045	0.106
	MILLER LT	0.006	0.005	0.005	0.006	0.003	0.005	0.005	0.010	0.010	0.019	0.017	0.020	0.019	0.018	0.012	0.030	-1.266

Table 5: Median Advertising Elasticities

Brewer	Beer	Bud	Bud Light	Busch Light	Michb	Michb Light	Coors	Coors Light	Kstone	Kstone Light	Old Style	Old St Light	Olymp	Pabst	MGD	MGD Light	High Life	Miller Lite
	Coverage (COV)	*0.96*	*0.95*	*0.82*	*0.94*	*0.92*	*0.93*	*0.95*	*0.72*	*0.76*	*0.54*	*0.52*	*0.59*	*0.72*	*0.95*	*0.87*	*0.95*	*0.95*
	SIZE	*0.41*	*0.42*	*0.47*	*0.29*	*0.29*	*0.40*	*0.42*	*0.44*	*0.45*	*0.41*	*0.48*	*0.46*	*0.43*	*0.36*	*0.39*	*0.39*	*0.43*
Anheuser-Busch	BUDWEISER	0.0177	0.0138	0.0007	0.0006	0.0022	0.0013	0.0141	0.0053	0.0050	-0.0003	0.0006	0.0002	0.0023	0.0012	0.0082	0.0018	0.0166
	BUD LT	0.0424	0.0326	-0.0002	0.0067	-0.0015	0.0112	-0.0046	0.0119	-0.0020	0.0009	-0.0018	0.0003	0.0051	0.0102	-0.0018	0.0165	-0.0034
	BUSCH LT	0.1115	-0.0124	0.0037	0.0136	-0.0032	0.0211	-0.0131	0.0415	-0.0040	0.0032	-0.0044	0.0008	0.0178	0.0412	-0.0066	0.0414	-0.0140
	MICHELOB	0.0267	0.1027	0.0068	0.0521	0.0399	0.0087	0.1075	0.0521	0.0473	-0.0028	0.0049	0.0016	0.0218	0.0161	0.0992	0.0140	0.1267
	MICHELOB LT	0.1461	-0.0418	-0.0019	0.0642	0.0316	0.0469	-0.0444	0.0580	-0.0131	0.0035	-0.0111	0.0019	0.0207	0.0543	-0.0128	0.0800	-0.0477
Adolph Coors	COORS	0.0334	0.0963	0.0070	0.0054	0.0157	0.0266	0.1216	0.0499	0.0404	-0.0027	0.0055	0.0012	0.0158	0.0096	0.0815	0.0138	0.1239
	COORS LT	0.0386	-0.0048	-0.0002	0.0070	-0.0014	0.0128	0.0356	0.0122	-0.0021	0.0012	-0.0031	0.0004	0.0051	0.0099	-0.0021	0.0157	-0.0056
	KEYSTONE	0.4538	0.3569	0.0248	0.0629	0.0510	0.1047	0.4052	0.1026	0.2052	0.0192	0.0218	0.0007	0.0087	0.1767	0.2552	0.1774	0.4526
	KEYSTONE LT	0.2709	-0.0330	-0.0012	0.0371	-0.0068	0.0540	-0.0380	0.1408	0.0515	0.0092	-0.0142	0.0025	0.0392	0.1060	-0.0148	0.0981	-0.0426
Bond	OLD STYLE	-0.3792	0.4093	0.0396	-0.0964	0.0830	-0.1047	0.4136	0.2923	0.2645	0.0041	0.1451	0.0075	0.0579	-0.0908	0.2122	-0.1790	0.4387
	O. STYLE LT	0.5477	-0.9079	-0.0417	0.1573	-0.1773	0.1716	-0.8905	0.2678	-0.2785	0.2674	0.0109	0.0116	0.0778	0.1431	-0.3332	0.2451	-1.0173
Pabst	OLYMPIA	0.3203	0.2663	0.0184	0.0697	0.0421	0.0947	0.2776	0.0333	0.1247	0.0147	0.0331	0.0011	0.0157	0.1026	0.1523	0.1508	0.3258
	PABST	0.2501	0.2065	0.0136	0.0635	0.0380	0.0766	0.2300	0.0103	0.0765	0.0047	0.0053	0.0007	0.0163	0.0813	0.1128	0.1207	0.2594
Philip Morris/Miller	MGD	0.0189	0.0605	0.0030	0.0044	0.0119	0.0050	0.0653	0.0253	0.0230	-0.0015	0.0026	0.0007	0.0104	0.0230	0.0392	0.0094	0.0746
	MGD LT	0.0933	-0.0103	-0.0005	0.0143	-0.0016	0.0133	-0.0111	0.0335	-0.0043	0.0034	-0.0048	0.0006	0.0171	0.0566	0.0407	0.0377	-0.0130
	HIGH LIFE	0.0208	0.0687	0.0036	0.0037	0.0119	0.0062	0.0697	0.0286	0.0257	-0.0013	0.0027	0.0009	0.0120	0.0059	0.0554	0.0403	0.0877
	MILLER LITE	0.0283	-0.0038	-0.0002	0.0057	-0.0012	0.0082	-0.0041	0.0092	-0.0015	0.0006	-0.0013	0.0003	0.0040	0.0081	-0.0017	0.0131	0.0291

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Appendix A: Selected Brands by Brewer (Acronym and Country of Origin)

Brewer	**Brand**	Brewer	Brand
Anheuser-Busch:	Budweiser	Grupo Modelo:	Corona
(AB, U.S.)	Bud Dry	(GM, Mexico)	
	Bud Light	Goya (GO, U.S.):	Goya
	Busch	Heineken:	Heineken
	Busch Light	(H, Netherlands)	
	Michelob	Labatt:	Labatt
	Michelob Dry	(LB, Canada)	Labatt Blue
	Michelob Golden Draft		Rolling Rock
	Michelob Light	Molson:	Molson
	Natural Light	(M, Canada)	Molson Golden
	Odoul's		Old Vienna
Adolph Coors:	Coors	Pabst:	Falstaff
(ADC, U.S.)	Coors Extra Gold	(P, U.S.)	Hamms
	Coors Light		Hamms Light
	Keystone		Olympia
	Keystone Light		Pabst Blue Ribbon
Bond Corp:	Black Label		Red White & Blue
(B, U.S.)	Blatz	Miller/Phillip Morris:	Genuine Draft
	Heidelberg	(PM, U.S.)	Meister Brau
	Henry Weinhard Ale		Meister Brau Light
	Henry Weinhard P. R.		MGD Light
	Kingsbury		Miller High Life
	Lone Star		Miller Lite
	Lone Star Light		Milwaukee's Best
	Old Style	Stroh:	Goebel
	Old Style Light	(S, U.S.)	Old Milwaukee
	Rainier		Old Milwaukee Light
	Schmidts		Piels
	Sterling		Schaefer
	Weidemann		Schlitz
	White Stag		Stroh
Genesee:	Genesee	FX Matts:	Matts
(GE, U.S.)	Kochs	(W, U.S.)	Utica Club

[a] These brands correspond to G. Hieleman Brewing Co., which was acquired in 1987 by Australian Bond Corporation Holdings; it is classified as a domestic brewer because this foreign ownership was temporary.

Appendix B: Data Description and Selection

IRI is a Chicago based marketing firm that collects scanner data from a large sample of supermarkets that is drawn from a universe of stores with annual sales of more than 2 million dollars. This universe accounts for 82% of all grocery sales in the U.S. In most cities, the sample of supermarkets covers more than 20% of the relevant population. In addition, IRI data correlates well with private sources in the Brewing Industry (the correlation coefficient of market shares for the top 10 brands between data from IRI and data from the Modern Brewery Age Blue Book is 0.95). Brands that had at least a 3% local market share in any given city were selected. After selecting brands according to this criterion, remaining observations are dropped if they had a local market share of less than 0.025%. Brands that appear in less than 10 quarters are also dropped. Also, if a brand appears only in one city in a given quarter, the observation for that quarter is not included. This is done because some prices in other cities are used as instruments.

The original dataset contains observations in 63 cities; five cities were dropped because of minimal number of brands or quantities. Overall, the number of cities increases over time; however, some cities appear only in a few quarters in the middle of the period. The average number of cities per quarter is 47. The variable *REG* was constructed as follows. First the percentage of cities in which each brand was present was averaged over time. A plot of these averages revealed two clusters of brands, one close to 100% (denoted national brands) and another (roughly) below 50% (denoted regional brands). The variable WAGES was constructed by averaging the hourly wages of interviewed individuals from the Bureau of Labor Statistics CPS monthly earning files at the NBER. For a given city-quarter combination, individuals working in the retail sector were selected for that city over the corresponding three months. The average was then calculated over the number of individuals selected.

Endnotes

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[1] The existence of possible stock effects was investigated but the estimated coefficients on lagged advertising expenditures were found not to be statistically different than zero.

[2] A logarithmic specification for advertising could not be used because of zero entries for some brands.

[3] The inverse measure of distance between brands *j* and *k* is defined as: 1/[1+2*(Euclidean distance between *j* and *k*)]. Euclidean distance in a one-dimensional space is the absolute difference in the value of the characteristic between *j* and *k*. In *n*-dimensional space, Euclidean distance is equal to $\sqrt{(j_1 - k_1)^2 + ... + (j_n - k_n)^2}$, where the subscript is the brand's coordinate in each of the *n*-dimensions.

[4] To keep simplicity in notation, distance measures (δ_{jk} and μ_{jk}) are depicted as market invariant. In the application, however, some distance measures vary by market.

[5] The number of continuous distance measures is limited by information on product characteristics.

[6] Beers could also be classified by lagers, ales, porters, and stouts. However, lagers account for over 90% of all sales in the U.S.

[7] Distance and weighing matrices were performed with *Matlab* algorithms, available upon request.

[8] IRI and LNA data was kindly provided by Ronald Cotterill, Director of the Food Marketing Policy Center at the University of Connecticut.

[9] Some states limit alcohol content (e.g. Oklahoma and Utah). In these cases, the alcohol content variable is a less accurate proxy for actual alcohol content. Inclusion of city dummies moderates this problem.

[10] Attempts to correct for spatial autocorrelation by assigning 'closeness' values to off-diagonal elements of the GMM weighing matrix were unsuccessful as we encountered a computational limitation when the number of non-zero elements of the already large $(T \times n) \times (T \times n)$ matrix $\hat{\Omega}$ increases.

[11] 95% confidence intervals were computed with 5,000 draws from the asymptotic distribution of the estimated coefficients.

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Food Marketing Policy Center
1376 Storrs Road, Unit 4021
University of Connecticut
Storrs, CT 06269-4021

Tel: (860) 486-1927
FAX: (860) 486-2461
email: *fmpc@uconn.edu*
http://www.fmpc.uconn.edu