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C Rojas

EB Peterson

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Christian Rojas [a,*], Everett B. Peterson [b]

[a] *Resource Economics Department at the University of Massachusetts-Amherst, United States*
[b] *Department of Agricultural and Applied Economics at Virginia Tech, United States*

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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. using the Distance Metric method of Pinkse, Slade and Brett [Pinkse, J., Slade, M., Brett, C., 2002. Spatial price competition: a semiparametric approach. Econometrica 70, 1111–1155]. Unlike previous studies, this work estimates the own- and cross-advertising elasticities in addition to price elasticities. 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. We discuss the implications of these results in this industry.

JEL classification: D12; L66; M37

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1. Introduction

Empirical analyses of issues in differentiated products markets often require the estimation of numerous demand elasticities. Some applications of price elasticity estimates include the delineation of markets, market power assessment, and the competitive effects of mergers. While brand-level advertising elasticities are less commonly estimated, they can be used to determine whether advertising is

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* Corresponding author. Tel.: +1 413 545 2496.
E-mail address: rojas@resecon.umass.edu (C. Rojas).

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predatory (it rearranges market shares) or cooperative (it shifts demand out). Determining the nature of advertising in the U.S. brewing industry is of particular interest because previous policy decisions on whether to allow advertising of alcoholic beverages have assumed that advertising is purely predatory.[1]

Estimating brand-level own- and cross-elasticities for many differentiated products is a difficult task due to the large number of unknown parameters to be estimated. A common approach used to address this dimensionality problem is to place restrictions on the cross-price coefficients. For example, neoclassical demand models, such as those used by Hausman et al. (1994), and Hausman (1996) 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. Aggregate versions of the discrete choice (DC) demand model reduce the number of coefficients by projecting the number of products on to a lower dimensional space, namely the product characteristics. Variants of the DC model are attractive because they explicitly model consumers' heterogeneity of preferences over product characteristics. The main drawbacks DC models are the independence of irrelevant alternatives (IIA) property in logit and nested logit models, the computational complexity of the random coefficients model, and the assumption that the consumer purchases a single unit of the differentiated product. This last assumption clearly does not fit consumer behavior in many differentiated product markets.

Pinkse et al. (2002) [henceforth PSB] developed the distance metric (DM) technique to overcome the dimensionality limitation of neoclassical demand models by specifying the cross-price terms as a function of a brand's location in product characteristic space relative to other brands. Various distance measures between brands may be constructed 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 advantages of the DM method are that it is easier to estimate than the random coefficient DC model; it allows testing the existence and strength of different product groupings as potential sources of competition; and it accounts for the location of brands location in product space.

In this paper, we employ the DM method to estimate the price and advertising elasticities of demand for 64 brands of beer in the United States. This is one of the first studies that estimates a large number of brand-level advertising elasticities.[2] In addition, controlling for brand advertising is important because it reduces the likelihood of common demand shocks across regions, which improves the validity of our identifying assumption for prices.

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. However, the former effect dominates 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.

2. Empirical model

Previous DM applications (Pinkse and Slade, 2004; Slade, 2004) employ a quadratic indirect utility function and use Roy's Identity to derive the uncompensated demand functions. If the

[1] See Elzinga (2000), Nelson (2005) and Tremblay and Tremblay (2005) for detailed descriptions of the U.S. brewing industry.

[2] Advertising in differentiated products has been investigated in markets with fewer brands. For example, Deighton, Henderson and Neslin (1994) study markets with less than 10 brands.

marginal utility of income is constant, which may be plausible when using cross-sectional or very short panel data, its value may be normalized to equal one, greatly simplifying the demand functions to be estimated. Because of the length of panel data we employ, 20 quarters, it is less plausible that the marginal utility of income is constant. Thus, the quadratic indirect utility function is less attractive because the uncompensated demand functions are non-linear in the parameters. Given the large number of brands, estimating a model that incorporates the DM method and is non-linear in the parameters is not practical. To solve this problem, we employ a linear approximation of the Almost Ideal Demand System (Deaton and Muellbauer, 1980):

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

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. Because the Stone price index is not invariant to changes in the units of measurement (Moschini, 1995) we specify a log-linear analogue of the Laspeyeres price index (P^L) to linearize the ALIDS. This index is defined as: $\log P_t^L = \sum_{j=1}^{n} w_j^o \log(p_{jt})$; where w_j^o is base share for brand j, which is defined as $\mathrm{w}_j^o = T^{-1}\sum_{t=1}^{T} w_{jt}$.

Following Sutton (1991: 45–16) 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 brewers' mass media advertising seldom informs consumers about price. Only the flow effects of advertising are included because in alternative model specifications with lagged advertising expenditures the estimated coefficients for lagged advertising expenditure were not statistically different than zero.

Advertising is incorporated into Eq. (1) through the intercept term a_{jt}^{*}, which is modified to equal: $a_{jt}^{*} = a_{jt} + \sum_{k=1}^{n} c_{jk}A_{kt}^{\gamma}$; where A_{kt} represents advertising expenditures of brand k in market t.[3] The parameter γ is included to account for decreasing returns to advertising. Following Gasmi et al. (1992), 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 this definition of a_{jt}^{*} into Eq. (1) and adding an error term:

$$w_{jt} = a_{jt} + \sum_{k=1}^{n} b_{jk} \log p_{kt} + \sum_{k=1}^{n} c_{jk} A_{kt}^{\gamma} + d_j \log(x_t/P_t^L) + \varepsilon_{jt}. \tag{2}$$

Eq. (2) can be interpreted as a first-order approximation in prices and advertising to the demand function that allows for unrestricted price and advertising parameters. With 64 brands, it would be impractical to estimate Eq. (2) without reducing the dimensionality of the model.

2.1. The distance metric (DM) method

The cross-price and cross-advertising coefficients (b_{jk} and c_{jk}) in Eq. (2) 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 may be used to

[3] A logarithmic specification for advertising is not possible due to zero entries for some brands.

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.[4] 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 PSB, we define the cross-price and cross-advertising coefficients as: $b_{jk}=g(\delta_{jk})$ and $c_{jk}=h(\mu_{jk})$, where δ_{jk} and μ_{jk} are the set of distance measures for price and advertising, respectively.[5] Then, Eq. (2) can be written as:

$$w_{jt} = a_{jt} + b_{jj}\log p_{jt} + c_{jj}A_{jt}^{\gamma} + \sum_{k \neq j}^{n} g(\delta_{jk})\log p_{kt} + \sum_{k \neq j}^{n} h(\mu_{jk})A_{kt}^{\gamma} + d_j \log(x_t/P_t^L) + \varepsilon_{jt}. \tag{3}$$

The functions g and h measure how the strength of competition between brands varies with distance measures and are specified as a linear combination of the distance measures:[6]

$$g = \sum_{l=1}^{L} \lambda_l \delta_{jk}^{l}, \text{ and} \tag{4}$$

$$h = \sum_{m=1}^{M} \tau_m \mu_{jk}^{m} \tag{5}$$

where λ and τ are coefficients to be estimated, and 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, $(n-1)$ equations can be estimated. However, if n is very large, then it may become impractical to estimate a large system of equations. One method to further 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 assumption is too restrictive, 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 Eq. (3) would be defined as $b_{jj}=b_1+b_2\text{ALC}_j$, where ALC_j is brand j's alcohol content (effectively interacting price with characteristics).

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[4] Closeness between brands j and k is defined as: $1/[1+2^*$ (Euclidean distance between j and k)]. The main results are not sensitive to alternative definitions of closeness.

[5] For simplicity, distance measures (δ_{jk}, μ_{jk}) are depicted as market invariant.

[6] As shown by PSB, a parametric specification may not always be consistent. Semi-parametric specifications of g and h indicated that the parametric version is not restrictive (see Rojas, 2005).

Combining Eqs. (3), (4), and (5) with the own-price and own-advertising interactions described above and after regrouping prices into L weighted terms and cross-advertising into M weighted terms, the empirical model is written as:

$$w_{jt} = a_{jt} + b_1 \log p_{jt} + \sum_{g=1}^{G} b_{g+1} \log p_{jt} PC_{gt}^{\mathrm{p}} + c_1 A_{jt}^{\gamma} + \sum_{h=1}^{H} c_{h+1} A_{jt}^{\gamma} PC_{ht}^{\mathrm{A}} + \tag{6}$$
$$+ \sum_{l=1}^{L} \left. \lambda_l \sum_{k \neq j}^{n} \delta_{jk}^{l} \log p_{kt} \right) + \sum_{m=1}^{M} \left. \tau_m \sum_{k \neq j}^{n} \mu_{jk}^{m} A_{kt}^{\gamma} \right) + d_j \log(x_t / P_t^L) + \varepsilon_{jt}$$

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.

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 $(n \times n)$ "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 $(n \times n)$ weighing matrix is multiplied by the $(n \times 1)$ vector of brand prices or advertising in each market one obtains the appropriate sum over $k \neq j$ in the share equation.

2.2. Continuous distance measures

Three continuous product characteristics are utilized in this study: alcohol content (ALC), product coverage (COV), and container size (SIZE).[7] Product coverage measures the fraction of the market that is covered by a brand. 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.

2.3. Discrete distance measures

Three different types of product grouping discrete distance measures are utilized: 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. The weighing matrices for the product segment, 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

[7] Limited information on product characteristics restricts the number of continuous measures.

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. This distance measure 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 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 whether two brands are their nearest neighbor (NN) in product space and if products share a common boundary (CB) in product space. Brands j and k share a common boundary if there is a set of points in product space that are at an equal distance from both brands and no other brand is closer to these points. (See Rojas (2005) for more details.) 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). The j,k element of these weighing matrices is equal to one if brands j and k share a common boundary (WCBAC and WCBCS) or are each other's nearest neighbor (WNNAC and WNNCS) 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. 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.

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.

2.4. 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. The main data source is the Information Resources Inc. (IRI) Infoscan Database. The IRI data includes prices and total sales for several hundred brands for up to 58 metropolitan areas (henceforth

Table 1
Description and summary of statistics of variables

Variable	Description	Units	Mean	Standard deviation	Min	Max
IRI database						
Price	Average (per brand) price	$/288 oz	12.1	3.87	0.82	28.9
Quantity	Volume sold	288 oz (000)	23.53	63.6	0.00	2652
UNITS	Number of units sold, regardless of size	(000)	57.88	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
Other variables						
A	Quarterly national advertising expenditures	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	$/h	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.

called 'cities' for simplicity) over 20 quarters (1988–1992). Volume sales (Q) 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 (Table 2). On average there are 37 brands sold in each city market with a minimum of 24 brands and a maximum of 48 brands.

In addition to price and sales data, the IRI database contains information on several 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. 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.

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 (especially Case et al., 2000). It is assumed that alcohol content remains constant for each brand.[8] The binary variable

[8] Some states limit alcohol content (e.g. Oklahoma). In these cases, the alcohol content variable is a less accurate proxy for actual alcohol content. City dummies moderate this problem.

Table 2
Selected brands by brewer (acronym and country of origin)

Brewer	Brand	Brewer	Brand
Anheuser–Busch: (AB, U.S.)	Budweiser	Grupo Modelo:	Corona
	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: (ADC, U.S.)	Coors	Pabst:	Falstaff
	Coors Extra Gold	(P, U.S.)	Hamms
	Coors Light		Hamms Light
	Keystone		Olympia
	Keystone Light		Pabst Blue Ribbon
Bond Corp[a]: (B, U.S.)	Black Label		Red White and Blue
	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: (GE, U.S.)	Genesee	FX Matts:	Matts
	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.

(REG) takes a value of one if brand j is a regional brand and zero if it is a national brand. A brand is defined as regional if it is only present in a few contiguous states.

4. Estimating the demand model

Given the strategic nature of price and advertising, all terms in Eq. (6) that contain these two variables are treated as endogenous. 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 Eq. (6) and θ the vector of parameters to be estimated. The generalized method of moments (GMM) estimator is used:

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

with consistent estimator for its asymptotic variance, $A\ \mathrm{var}(\hat{\theta}_{\mathrm{GMM}})=(S'P_z S)^{-1}$; where, $P_z=Z(Z'\hat{\Omega}Z)^{-1}Z'$, and $\hat{\Omega}$ is a $(T\times n)\times(T\times n)$ "weighing" matrix.

The GMM estimator can accommodate and correct for the presence of heteroskedasticity and correlation of unknown form through elements of the weighing matrix. The off-diagonal element j,k is defined as: $\hat{\Omega}_{j,k}=\hat{\varepsilon}_j\hat{\varepsilon}_k$ if the pair of observations (j,k) are suspected to be correlated, and zero otherwise. The diagonal elements are defined as $\hat{\varepsilon}_j^2$ to incorporate heteroskedasticity. Note that $\hat{\varepsilon}$ is the residual obtained from a 'first step' *2-stage least squares* regression. We accommodate for the presence of temporal (one lag) and spatial (across cities and across brands) correlation.[9]

4.1. Instruments

Two different identification assumptions are utilized: after controlling for brand, city, and time specific effects, demand shocks are independent across cities and across time. We employ both assumptions to address price endogeneity and the second to address the endogeneity of advertising and product coverage.

Because beer is produced in large-scale plants and then distributed to various markets, the price of a given brand will be correlated across markets due to a common marginal cost. If the demand shocks are independent across cities, prices will not be correlated with demand shocks in other markets and can hence be used as instruments for other markets. A potential problem in using prices in other cities as instruments is that beer is costly to transport. This could result in poor correlation between prices in a city that is distant to the nearest brewing facility and prices in cities that are more closely located to a brewing facility. This appears not to be the case in our data for two reasons. First, the brewers included in our sample have multiple plants located throughout the United States. Second, we tested for the possibility of this "transportation cost" effect by including an instrumental variable for price that measures a brand's distance from its nearest plant. The coefficient on this distance variable in the first stage regression of price on all included and excluded instruments was statistically insignificant, suggesting that, after controlling for other factors, transportation costs are not an important price determinant.

The inclusion of national advertising expenditures and time dummy variables further reduces the potential that demand shocks may be correlated across markets. The inclusion of advertising expenditures controls for advertising related demand shocks that may be correlated across markets. The inclusion of time dummy variables controls for any other unobserved national demand shock. In addition, we include brand dummies to control for unobserved product characteristics that are invariant across markets (e.g. brand loyalty, status) and are likely to be correlated with the error term (Berry, 1994; Nevo, 2001). Finally, the IRI data employed in this study is based on broadly defined city/regional markets which further reduce the possibility of potential correlation between the unobserved shocks across markets.

To assess the robustness of our results, we first utilize the identifying assumption of independence of demand across markets and then the assumption of independence of demand across time (using lagged prices as instruments). We also conduct a test of instrument exogeneity that is valid in the presence of temporal and spatial correlation and particularly suitable for this application where price enters the demand equation in several variables (interacted and weighted

[9] Tests on estimates of the error term (i.e. residuals) from GMM estimation without this correction suggested the presence of temporal and spatial error correlation.

terms). The test, developed by PSB (see Pinske and Slade: p. 627–628), is similar to a GMM differential test in which the error-orthogonality of a subset of "suspicious" instruments is tested. In this application we conduct two instrument exogeneity tests: one in which the suspicious instruments are those constructed with lagged price and the non-suspicious instruments are those constructed with average price in other cities, and another in which suspicious instruments are those constructed with average price in other cities and the non-suspicious instruments are those constructed with lagged price.

Following Nevo (2001), we also create proxies for city-specific marginal costs that are used as additional price instruments to conduct overidentifying tests. 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.

Because national brand-level advertising expenditures are invariant across markets, we utilize the second identifying assumption and use lagged advertising expenditures as instruments for advertising. 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. However, a brewer that advertises more might have a larger product coverage and if advertising is correlated with the error term, then coverage should not be treated as an exogenous variable. We instrument coverage using its lagged value. Coverage in neighboring cities was also considered as an instrument but it turned out to be a very poor one.

5. Results

Given the large number of possible distance measures and high levels of collinearity between these measures, 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 Eq. (6) in which either one cross-price term or one cross-advertising term is specified. Table 3 reports the estimated coefficients and *t-statistics* on the weighted cross-term using each of the distance measures.

First, one- and two-dimensional continuous distance measures for 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 closeness in alcohol content and product coverage is important for weighting rival prices while closeness in product coverage and container size is important for weighting rival advertising expenditures. Results for the two-dimensional distance measures indicate that closeness in alcohol content-product coverage and product coverage-container size space are 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, 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. Switching the relevant product spaces, alcohol content-product coverage for advertising and product coverage-container size for price, did not lead to changes in our main results.

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

Table 3
Estimated coefficient on weighted prices and weighted advertising from separate OLS regressions[a]

Distance measure (weighing matrix acronym)	Rival price[b]		Rival advertising	
	Coefficient	*t*-statistics	Coefficient	*t*-statistics
Continuous distance measures				
One-dimensional				
Alcohol content (WALC)	1.42**	2.39	0.02	0.44
Product coverage (WCOV)	7.65*	41.02	0.43*	57.56
Container size (WSIZE)	0.23	0.74	0.21*	11.37
Two-dimensional				
Alcohol content − product coverage (WAC)	10.84*	27.30	0.78*	43.22
Alcohol content − container size (WAS)	1.28**	2.42	0.17*	4.93
Product coverage − container size (WCS)	8.28*	30.51	0.58*	49.79
Discrete distance measures				
Common boundary (CB)				
Alcohol content − product coverage (WCBAC)	0.83**	2.08		
Alcohol content − product coverage − price (WCBACP)	5.20*	12.10		
Product coverage − container size (WCBCS)			0.38*	32.70
Product coverage − container size – price (WCBCSP)			0.53*	25.05
Nearest neighbor (NN)				
Alcohol content – product coverage (WNNAC)	11.19*	20.68		
Alcohol content − product coverage − price (WNNACP)	2.60*	4.73		
Product coverage − container size (WNNCS)			0.50*	25.21
Product coverage − container size − price (WNNCSP)			0.39*	14.77
Product groupings				
National Identity (WREG)	62.59*	4.49	0.92***	1.70
Brewer identity (WBREW)	29.28*	6.41	−0.29**	−2.12
Product classification 1[c] (WPROD1)	−2.07	−0.17	−1.08*	−7.84
Product classification 2 (WPROD2)	116.70*	7.51	−1.89*	−7.46
Product classification 3 (WPROD3)	19.36	0.56	−2.88*	−13.66
Product classification 4 (WPROD4)	−82.75*	−4.87	−2.03*	−4.42
Product classification 5 (WPROD5)	−42.85**	−2.35	−0.31**	−1.96

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

[a] Each coefficient (and its *t*-statistic) is obtained from a separate OLS regression of Eq. (6) 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.

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 and the negative coefficient on rival advertising weighted by brewer identity indicate that consumers are more apt to substitute between brands of the same firm. The positive coefficient on rival prices weighted by WREG indicates closer rivalry among regional brands. However, the positive coefficient on rival advertising weighted by WREG suggests the existence of cooperative effects of advertising among regional brands.

Because brands that belong to the same product segment should be substitutes, the estimated coefficient on rival prices weighted by product segment should be positive. The only positive coefficient that is statistically significant for rival prices is that of product classification 2

(WPROD2): light and regular beers. For rival advertising, the coefficients on all product segments are negative. The largest and most significant coefficient is that of product classification 3 (WPROD3). This classification is similar to 2 except that it includes the “budget” category in addition to light and regular.

5.1. Brand share equation

Results from OLS regressions in Table 3 were used to guide the choice of the variables that enter our final specification. However, when pooled into a single regression, some distance measures were highly collinear. Rival prices weighted by alcohol content-product coverage (WAC) and rival advertising expenditures weighted by product coverage-container size (WCS) were highly collinear. Weighing rival advertising expenditures by container size only (WSIZE) reduced this problem while not affecting the other parameter estimates. The common boundary distance measure in alcohol content-product coverage-price space (WCBACP) is highly collinear with other distance measures for rival prices and is omitted.

Table 4 reports the estimates of two OLS and four GMM regressions using the final choice of variables. In all models considered, the estimated coefficient for rival advertising expenditures weighted by brewer identity (WBREW) is not statistically significant than zero and its value is not reported in Table 4. Product classification 2 (WPROD2) is used to weight rival prices while product classification 3 (WPROD3) is used to weight rival advertising expenditures because this specification had the highest explanatory power. Model specifications that used the same product classification for weighing rival price and advertising were also considered but did not yield significant changes in the estimated parameters.

The results for the six different models in Table 4 track the effect of different endogeneity controls on the magnitude and significance of coefficients. The difference between the first and second OLS specifications is the inclusion of brand dummies. In addition to including brand dummies, all GMM specifications instrument for price and advertising, while GMM (3) and GMM (4) also account for the endogeneity of product coverage. GMM (1) and GMM (3) use prices in other cities as instruments while GMM (2) and GMM (4) use lagged prices as instruments. All models contain time and city/market binary variables (estimated coefficients not reported).

The only variable that is statistically significant in the constant 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.

The estimated coefficients for own-price, own-advertising, and their interactions with product characteristics are reported in the second group in Table 4. Because price and advertising are highly correlated with their corresponding interactions with product coverage, the inverse of this latter variable ($1/\mathrm{COV}$) 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 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

Table 4
Results of demand model estimation

Dependent variable: sales share (w_{jt})	OLS (1)		OLS (2)		GMM (1)		GMM (2)		GMM (3)		GMM (4)	
Variable; description	Coefficient	*t*-statistic [a]	Coefficient	*t*-statistic [a]	Coefficient [b]	*t*-statistic [b]	Coefficient [b]	*t*-statistic [b]	Coefficient [b]	*t*-statistic [b]	Coefficient [b]	*t*-statistic [b]
Constant a_{jt}												
Brand dummies	no		yes		yes		yes		yes		yes	
NCB: alcohol-coverage (AC) space [c]	−4.05	−3.10	−2.93	−2.76	−2.61	−2.23	−2.93	−2.34	−0.73	−0.57	−0.74	−0.58
Own price (b) and own-advertising (c)												
log$P$	−119.36	−13.88	−232.19	−14.89	−238.70	−3.23	−286.6	−9.22	−296.29	−3.43	−273.25	−8.97
log$P\times$(1/coverage)	−0.88	−4.66	−0.88	−3.48	−1.00	−2.47	−1.00	−2.51	−1.06	−2.54	−0.97	−2.49
log$P\times NCB$: coverage-size–price space	−7.12	−14.08	−5.66	−13.52	−6.24	−7.09	−6.42	−9.34	−13.72	−7.89	−13.56	−9.72
A^{γ}	7.08	36.21	1.47	9.51	1.30	4.08	1.30	3.80	3.23	3.82	3.23	3.83
$A^{\gamma}\times$(1/coverage)	−0.59	−9.39	−0.23	−6.90	−0.17	−2.22	−0.24	2.66	−0.21	−2.25	−0.21	−2.27
$A^{\gamma}\times$NCB: coverage-size (CS) space	−0.26	−7.60	−0.18	−6.83	−0.16	−3.75	−0.16	−3.60	−0.62	−3.22	−0.62	−3.23
Weighted cross price and weighted cross-advertising terms (λ_l and τ_m)												
Distance measures for price (weighing matrix acronym)												
Alcohol-coverage space (WAC)	3.32	21.94	5.29	12.72	4.57	5.91	4.92	6.03	3.65	4.05	3.80	4.32
Nearest neighbor: AC space (WNNAC)	−4.67	−11.62	3.35	8.85	3.43	5.26	3.19	4.73	5.69	4.72	5.26	4.47
Brewer identity (WBREW)	5.52	2.76	17.45	5.49	16.41	2.42	17.65	2.45	14.59	1.98	15.78	2.22
Product classification 2 (WPROD2)	45.65	6.86	76.90	3.65	106.64	2.52	110.00	2.42	128.92	2.88	114.02	2.60
National Identity (WREG)	38.01	5.25	48.14	6.59	52.68	4.11	57.63	3.54	51.99	3.80	54.67	3.42

Weighted cross price and weighted cross-advertising terms (λ_l and τ_m)												
Distance measures for advertising (weighing matrix acronym)												
Container Size, (WSIZE)	0.14	7.50	0.02	0.91	0.06	2.07	0.07	2.14	0.10	2.79	0.10	2.88
Common boundary CSP space(WCBCSP) [d]	0.79	17.72	0.57	15.53	0.62	10.65	0.61	10.46	1.37	8.74	1.37	8.72
Nearest neighbor: CS space (WNNCS)	0.55	28.12	0.33	19.75	0.39	14.94	0.39	14.11	0.36	10.08	0.37	10.20
Product Classification 3: (WPROD3)	−1.31	−8.99	−2.61	−11.33	−3.45	−6.27	−3.56	−5.85	−3.48	−5.56	−3.48	−5.63
National Identity (WREG)	−1.78	−15.64	0.80	1.63	4.53	1.89	4.63	1.77	4.32	1.68	4.16	1.62
Price index (d)												
$\log(x_t/P_t^L)$	5.36	0.64	12.66	1.95	32.14	0.81	39.36	1.03	37.51	0.59	33.01	0.85
Price instrument	No		No		Other city prices		Lagged prices		Other city prices		Lagged prices	
Advertising instrument	No		No		Lagged advert		Lagged advert		Lagged advert		Lagged advert	
Coverage instrument	No		No		No		No		Lagged coverage		Lagged coverage	
R^2 (centered)	0.60		0.76		0.76 (0.66)		0.76 (0.66)		0.75 (0.66)		0.75 (0.65)	
J-statistic (p-value)					1.01 (0.60)		0.83 (0.66)		1.47 (0.48)		1.40 (0.49)	
# observations	33,892		33,892		33,892		30,996		30,996		30,996	

Coefficients in table are original coefficients $\times 10^4$. All specifications include time and city dummies (not reported).

[a] Heteroskedasticity-robust.

[b] Corrected for heteroskedasticity, and temporal (one lag) and spatial (across cities and across brands) correlation.

[c] NCB is number of common boundaries.

[d] CSP is coverage-size-price space.

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 the two OLS models, 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% in model OLS (2) compared to model OLS (1). Instrumentation of price and advertising in the two GMM models further increases the absolute value of the price coefficient and decreases the magnitude of the advertising coefficient, albeit at a smaller scale. This finding is consistent with previous work (Nevo, 2001: Table V) and suggests that a major portion of the endogeneity bias is accounted by time invariant brand loyalty/valuation. Since the endogeneity of price, advertising and coverage needs to be accounted for, the remainder of the discussion focuses on the GMM models.

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. The next section contains a more extensive discussion on cooperative vs. predatory advertising.

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.

Overall, all GMM specifications have coefficients of the same magnitude and sign. An important difference is the magnitude of the price coefficient, which is about 14–24% smaller in GMM (1) than in the other GMM specifications. The advertising coefficient (A^{γ}) is 150% larger when product coverage is treated as an endogenous variable in GMM (3) and GMM (4). The importance of including advertising in the model was investigated by estimating a version of the model without advertising. This lead to reductions in the absolute value of the own-price coefficients of approximately 10%. There were also some differences in the cross-price coefficients but the overall differences in cross-price elasticities were minimal.

The goodness-of-fit measures are almost identical across all GMM specifications. The over-identification test suggests that lagged prices (GMM (2) and GMM (4)) might be slightly better instruments than prices in other cities. Models that used both sets of price instruments were also considered but their estimates (not shown) are qualitatively similar to using only one set of instruments.[10]

[10] An over-identification test rejects the validity of instruments when both sets of instruments are included. We suspect that when the number of over-identifying restrictions is large, the power of this test may be low.

5.2. Exogeneity tests

Two exogeneity tests for the for price instruments were conducted (see Pinske and Slade: p. 627–628). In one test, the non-suspect instruments are assumed to be prices in other cities and the suspect instruments are lagged prices. In the second test, the non-suspect instruments are assumed to be lagged prices and the suspect instruments are prices in other cities. The *p*-value for both tests is less than 0.01, suggesting that either set of price instruments is valid.

5.3. Elasticities

The estimated elasticities are consistent across the GMM models: the median own-price elasticities range from −3.726 to −3.201 while the median own-advertising elasticities range from 0.006 to 0.026. Focusing on model GMM (4), the median own-price elasticity across all brands is −3.53 and the median own-advertising elasticity is 0.006. All own-price elasticities are negative while approximately 53% of own-advertising elasticities are positive. All cross-price elasticities are positive and have a median value of 0.0527 whereas 74% of cross-advertising elasticities are positive and have a median of 0.010. 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 5 and 6 contain a sample of the median values of the price and advertising elasticities for selected brands using GMM (4). 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 5 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 5) indicate that all price elasticities are significantly different than zero at the 5% level.[11]

The median advertising elasticities vary considerably across brands. Approximately 78% of the advertising elasticity estimates are statistically different than zero at the 5% level. 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. In general, positive and negative cross-advertising elasticities have the same order of magnitude, but there are more positive cross-advertising elasticities than negative cross-advertising elasticities (74% vs. 26%), indicating that cooperative effects appear to dominate predatory effects. This pattern is present when either set of GMM estimates in Table 3 is used to compute elasticities, suggesting that cooperative advertising is robust to either identification assumption. Moreover, this result is also obtained with OLS (2) estimates and, to a lesser extent, with OLS (1) estimates.

[11] 5000 random draws are taken from the estimated variance–covariance matrix of the model parameters, which are assumed to be distributed jointly normal. 95% intervals were computed using the sample of elasticities that result from all draws.

Table 5
Median price elasticities

	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
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
Anheuser–Busch	BUDWEISER	−1.165	0.006	0.004	0.004	0.003	0.005	0.004	0.005	0.005	0.004	0.004	0.004	0.002	0.002	0.001	0.003	0.003
	MICHELOB	0.055	−2.698	0.060	0.043	0.028	0.041	0.052	0.066	0.072	0.035	0.036	0.036	0.023	0.024	0.011	0.029	0.025
Adolph Coors	COORS	0.038	0.051	−2.412	0.064	0.033	0.035	0.043	0.059	0.063	0.020	0.026	0.020	0.046	0.046	0.013	0.029	0.022
	KEYSTONE	0.134	0.126	0.197	−6.188	0.103	0.151	0.128	0.125	0.129	0.073	0.081	0.076	0.146	0.147	0.040	0.089	0.082
Bond	OLD STYLE	0.242	0.245	0.242	0.283	−16.13	0.290	0.281	0.256	0.256	0.104	0.120	0.110	0.095	0.112	0.377	0.095	0.119
Pabst	OLYMPIA	0.092	0.088	0.085	0.123	0.081	−5.169	0.167	0.088	0.097	0.053	0.054	0.055	0.052	0.053	0.041	0.052	0.058
	PABST	0.075	0.092	0.092	0.073	0.033	0.142	−4.144	0.091	0.101	0.041	0.040	0.043	0.042	0.040	0.011	0.040	0.045
Philip Morris/Miller	MGD	0.024	0.034	0.034	0.021	0.017	0.019	0.028	−1.887	0.050	0.012	0.012	0.012	0.012	0.011	0.006	0.021	0.025
	HIGH LIFE	0.031	0.041	0.041	0.023	0.015	0.021	0.030	0.054	−1.921	0.013	0.013	0.013	0.013	0.013	0.005	0.027	0.026
Anheuser–Busch	BUD LT	0.008	0.008	0.005	0.005	0.002	0.005	0.005	0.005	0.005	−1.374	0.029	0.035	0.036	0.028	0.018	0.023	0.029
	BUSCH LT	0.025	0.024	0.017	0.018	0.006	0.016	0.017	0.017	0.017	0.099	−2.237	0.098	0.098	0.102	0.055	0.073	0.079
	MICHB LT	0.040	0.039	0.026	0.027	0.012	0.033	0.025	0.026	0.026	0.172	0.124	−2.782	0.166	0.141	0.104	0.144	0.142
Adolph Coors	COORS LT	0.006	0.006	0.012	0.011	0.004	0.005	0.006	0.006	0.006	0.037	0.033	0.035	−1.394	0.036	0.036	0.025	0.030
	KEYST LT	0.043	0.042	0.088	0.090	0.020	0.042	0.041	0.042	0.042	0.241	0.242	0.244	0.300	−4.082	0.141	0.184	0.195
Bond	O.STYLE LT	0.113	0.108	0.107	0.134	0.945	0.133	0.108	0.107	0.107	0.966	0.941	0.963	0.974	1.080	−17.936	0.598	0.953
Philip Morris/Miller	MGD LT	0.016	0.016	0.016	0.017	0.009	0.017	0.016	0.028	0.028	0.064	0.070	0.066	0.065	0.065	0.052	−2.043	0.097
	MILLER LT	0.005	0.005	0.005	0.005	0.002	0.005	0.004	0.009	0.009	0.021	0.019	0.021	0.022	0.020	0.014	0.030	−1.294

Table 6
Median advertising elasticities

	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
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
Anheuser–Busch	BUDWEISER	0.0174	0.0099	0.0004	−0.0005	0.0015	−0.0004	0.0104	0.0033	0.0032	−0.0006	0.0002	0.0001	0.0016	−0.0003	0.0055	−0.0006	0.0126
	BUD LT	0.0309	0.0323	−0.0008	0.0044	−0.0038	0.0074	−0.0153	0.0075	−0.0072	0.0003	−0.0026	0.0002	0.0034	0.0070	−0.0080	0.0115	−0.0107
	BUSCH LT	0.0716	−0.0493	0.0037	0.0090	−0.0092	0.0134	−0.0538	0.0275	−0.0174	0.0012	−0.0064	0.0005	0.0114	0.0266	−0.0272	0.0275	−0.0552
	MICHELOB	−0.0187	0.0664	0.0045	0.0517	0.0314	−0.0055	0.0698	0.0342	0.0304	−0.0053	0.0018	0.0011	0.0148	−0.0031	0.0668	−0.0071	0.0827
	MICHELOB LT	0.0954	−0.0946	−0.0049	0.0556	0.0312	0.0315	−0.0971	0.0376	−0.0338	0.0013	−0.0157	0.0013	0.0141	0.0404	−0.0520	0.0562	−0.1059
Adolph Coors	COORS	−0.0135	0.0668	0.0045	−0.0038	0.0103	0.0262	0.0896	0.0318	0.0261	−0.0059	0.0021	0.0008	0.0105	−0.0031	0.0567	−0.0042	0.0929
	COORS LT	0.0285	−0.0150	−0.0009	0.0045	−0.0037	0.0088	0.0349	0.0077	−0.0075	0.0004	−0.0046	0.0002	0.0034	0.0072	−0.0088	0.0115	−0.0144
	KEYSTONE	0.2910	0.2289	0.0166	0.0408	0.0328	0.0699	0.2639	0.1025	0.1685	0.0072	0.0086	−0.0006	−0.0120	0.1141	0.1716	0.1166	0.2924
	KEYSTONE LT	0.1748	−0.1355	−0.0047	0.0242	−0.0192	0.0362	−0.1513	0.1088	0.0512	0.0034	−0.0206	0.0017	0.0264	0.0693	−0.0622	0.0640	−0.1656
Bond	OLD STYLE	−0.7749	0.1536	0.0149	−0.2031	0.0309	−0.2219	0.1561	0.1305	0.1021	0.0056	0.1171	0.0031	0.0235	−0.1761	0.0817	−0.3778	0.1635
	O. STYLE LT	0.2041	−1.2974	−0.0592	0.0586	−0.2398	0.0640	−1.3269	0.1259	−0.4294	0.2210	0.0128	0.0052	0.0304	0.0533	−0.4297	0.0938	−1.4628
Pabst	OLYMPIA	0.2107	0.1731	0.0128	0.0465	0.0279	0.0642	0.1899	−0.0143	0.0903	0.0063	0.0177	0.0012	−0.0036	0.0678	0.1022	0.1022	0.2141
	PABST	0.1646	0.1343	0.0090	0.0446	0.0269	0.0542	0.1566	−0.0164	0.0525	0.0019	0.0021	−0.0002	0.0164	0.0554	0.0763	0.0853	0.1817
Philip Morris/ Miller	MGD	−0.0070	0.0418	0.0020	−0.0009	0.0089	−0.0018	0.0458	0.0162	0.0148	−0.0029	0.0010	0.0004	0.0070	0.0226	0.0307	−0.0014	0.0540
	MGD LT	0.0677	−0.0415	−0.0017	0.0098	−0.0051	0.0095	−0.0442	0.0212	−0.0166	0.0014	−0.0070	0.0004	0.0113	0.0472	0.0401	0.0305	−0.0499
	HIGH LIFE	−0.0070	0.0520	0.0024	−0.0018	0.0087	−0.0019	0.0516	0.0183	0.0164	−0.0026	0.0010	0.0006	0.0083	−0.0009	0.0426	0.0394	0.0707
	MILLER LITE	0.0258	−0.0055	−0.0006	0.0038	−0.0029	0.0062	−0.0087	0.0059	−0.0053	0.0002	−0.0019	0.0002	0.0027	0.0066	−0.0066	0.0113	0.0288

6. Summary and discussion

Much of the previous research on U.S. brewing has utilized firm-level data or data for a limited number of brands. The results of this previous research has been mixed regarding the nature of advertising rivalry among firms or brands with some results indicating cooperative and some indicating predatory behavior (Nelson, 2005: 281–288). Using a more complete set of brands, our results indicate that, in general, advertising is cooperative in the U.S. brewing industry. However, advertising rivalry does exist within the light beer product segment, as evidenced by the existence of negative cross-advertising elasticities. Thus, the earlier mixed results on advertising rivalry may have been due to focusing on inter-firm rivalry rather than on inter-brand rivalry with product segments.

In other markets, advertising has been found to be mainly predatory. Seldon and Doroodian (1990) find that firm advertising in the cigarette industry is “purely” predatory (i.e. own-advertising increases own-sales and decreases rivals’ sales, but overall sales remain constant). Slade (1995) finds that advertising among 4 saltine crackers is “mildly” predatory (i.e. own-advertising increases own-sales and decreases rivals’ sales, but overall sales increase). Our, results, on the other hand, indicate that both types of advertising can coexist in a market.

The generally cooperative nature of traditional advertising suggests it stimulates the overall demand for beer. This is contrary to earlier literature that advertising does not stimulate the demand for beer (Nelson, 1999; Nelson and Moran, 1995; Lee and Tremblay, 1992; 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) (Center for Science in the Public Interest, 1983). The FTC dismissed the petition on the grounds that advertising does not increase the consumption of alcoholic beverages.

The results in this paper can also be utilized to test alternative hypotheses of brand pricing behavior and market power (Rojas, in press). 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 elasticity estimates.

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