Modeling Advertising Expenditures and Spillover Effects Applied to the U.S. Non-Alcoholic Beverage Industry: Vector Autoregression (VAR) and Polynomial Distributed Lag (PDL) Approaches

Senarath Dharmasena
Oral Capps, Jr.
David A. Bessler

**Agribusiness, Food and Consumer Economics Research Center (AFCERC), and Department of Agricultural Economics,
Texas A&M University, College Station, TX 77843-2124**

Selected Paper Presented at the Agricultural and Applied Economics Association Annual Meeting, Seattle, Washington, August 12-14, 2012

Modeling Advertising Expenditures and Spillover Effects Applied to the U.S. Non-Alcoholic Beverage Industry: Vector Autoregression (VAR) and Polynomial Distributed Lag (PDL) Approaches

JEL Classification: C18, C22, C52, C53, C81, D11, D12

Abstract

The non-alcoholic beverage market in the U.S. is a multi-billion dollar industry growing steadily over the past decade. Also, non-alcoholic beverages are among the most heavily advertised food and beverage groups in the United States. Several studies pertaining to non-alcoholic beverages including the incorporation of advertising effects have been conducted, but most of these have centered attention on milk consumption. Some studies have considered demand interrelationships for several beverages including advertising effects in systems-wide analyses.

In our analysis, we develop and employ a unique monthly time-series data set derived from Nielsen Homsescan panels for household purchases of non-alcoholic beverages over the period from January 1998 through December 2009. This data set is subjected to the use of vector autoregression (VAR) and polynomial distributed lags (PDL) to examine own-advertising and cross-advertising effects for non-alcoholic beverages. Contemporaneous causal structures among advertising expenditures, quantities and prices of various non-alcoholic beverages also are studied using artificial intelligence approaches such as directed acyclic graphs (DAGs).

Once the VAR and PDL (through augmenting the AIDS model) are estimated, we can ascertain own- and cross-advertising effects of various beverages. Impulse response functions gleaned from the use of the VAR approach would show us the impacts of advertising expenditures of various beverages to a one-time-only shock. The direction and the strength of the impulse would speak to the effect of the adverting expenditure of one beverage on others. Error variance decompositions help us determine the magnitude of the contribution of advertising expenditures of several beverages on a given beverage.

Similarly, own- and cross-adverting expenditure elasticities generated through the PDL help us determine the negative and positive spillover effects of advertising expenditure of one beverage on several others. The contemporaneous causal structure pertaining to advertising expenditures, quantities and prices of various beverages help identify endogenous, exogenous and/or weakly exogenous factors. Ultimately, the better model to ascertain the effect of advertising expenditures of various non-alcoholic beverages is identified through the study of out-of-sample forecasts generated though both models.

Key Words: non-alcoholic beverages, vector autoregression, polynomial distributed lags, beverage advertizing, directed acyclic graphs

Modeling Advertising Expenditures and Spillover Effects Applied to the U.S. Non-Alcoholic Beverage Industry: Vector Autoregression (VAR) and Polynomial Distributed Lag (PDL) Approaches

JEL Classification: C18, C22, C52, C53, C81, D11, D12

Background

The non-alcoholic beverage market in the U.S. is a multi-billion dollar industry growing steadily over the past decade (American Beverage Association, 2011). This growth is attributed not only to traditional beverages like soft drinks, milk, fruit beverages, tea and coffee, but also new-age wellness and functional beverages such as energy drinks, sports drinks, sparkling and non-sparkling water, and enhanced (bottled vitamin water) water, flavored milk, soy beverages, coconut water, and various other ready-to-drink beverages (Beverage Marketing Corporation, 2011).

Advertising expenditures, both generic and branded, on non-alcoholic beverages total on average to roughly $2 billion per year (Zheng and Kaiser, 2008). As a result, non-alcoholic beverages are among the most heavily advertised food and beverage groups in the United States. However, advertising and promotion expenditures for a particular non-alcoholic beverage potentially may influence not only the demand for that beverage but also the demand for related beverages, either negatively or positively. For example, advertising and promotion expenditures directed to regular soft drinks may increase the demand for that particular category, while decreasing demand for competing beverages such as bottled water or sports drinks. This cross-product advertising effect is called the "spillover effect". Negative-type spillover effects are detrimental for beverage companies who are trying to sell both products such as regular soft drinks and bottled water (for example Coca Cola® Company sells both regular Coke® and Dasani® bottled water). Therefore, identifying the appropriate spillover effects of advertising is crucial for beverage manufacturers and marketers so that appropriate advertising strategies can be formulated.

Several studies pertaining to non-alcoholic beverages including the incorporation of advertising effects have been conducted, but most of these have centered attention on milk consumption (Kinnucan and Forker, 1986; Kaiser and Roberte, 1996). Some studies have consid ered demand interrelationships for several beverages including advertising effects in systems-wide analyses (Gao and Lee, 1995 for three different juices; Kinnucan *et al.*, 2001 for milk, juice, soft drinks, and tea/coffee; Zheng and Kaiser, 2008 for milk, juice, soft drinks, bottled water, and coffee/tea). Kinnucan *et al.* (2001) used annual time-series data for the United States from 1970 through 1994, and Zheng and Kaiser (2008) used annual time-series data from 1974 through 2005 in estimating impacts of advertising on the demand for non-alcoholic beverages.

In our analysis, we develop and employ a unique *monthly time-series data* set derived from Nielsen Homsescan panels for household purchases of non-alcoholic beverages over the period from January 1998 through December 2009. This data set is subjected to the use of vector autoregression (VAR) and polynomial distributed lags (PDL) to examine own-advertising and cross-advertising effects for non-alcoholic beverages. Contemporaneous causal structures among advertising expenditures, quantities and prices of various non-alcoholic beverages also are studied using artificial intelligence approaches such as directed acyclic graphs (DAGs) (Swanson and Granger, 1997; Bessler and Akleman, 1998; Sprites, Glymour and Scheines, 2000).

The specific categories of non-alcoholic beverages considered are soft drinks (regular and diet combined), milk (skim, low-fat and whole combined), fruit beverages (fruit juices and fruit drinks), and coffee/tea. According to our knowledge, this work is the first attempt to model advertising effects on demand for non-alcoholic beverages using the aforementioned dynamic modeling approaches. Novelty also spans across our data set wherein we use a monthly time-series in contrast to annual time-series used in past studies.

The objectives are fourfold: (1) to estimate own- and cross-advertising elasticities associated with the aforementioned non-alcoholic beverages using PDL approach; (2) to estimate impulse response functions, error variance decompositions, and contemporaneous causal patterns associated with aforementioned non-alcoholic beverages using the VAR and the DAG approaches; and (3) to assess positive and negative spillover effects associated with the advertising and promotion of the respective non-alcoholic beverages using both approaches; (4)

to perform a model competitiveness exercise using out-of-sample forecasts generated from the VAR and PDL approaches.

Methodology

To capture carryover effects inherent with the use of advertising and promotion expenditures, we plan to use VAR and PDL models. Impulse response functions and error variance decompositions pertaining to advertising expenditures of various beverages are generated. The contemporaneous causal patterns among advertising expenditures, quantities and prices of aforementioned beverages are modeled using DAGs.

For the PDL model the degree of the polynomial, the length of the lag, and the use of endpoint restrictions may vary from one non-alcoholic beverage to another. We build into the almost ideal demand system (AIDS) model the flexibility of ascertaining the appropriate lag structure for each of the non-alcoholic beverages considered. We choose the lag structures on the basis of the Schwarz or Akaike Information Criteria (SIC, AIC). Both VARs and PDLs are modeled using 120 monthly data points; we save 24 monthly data points for generating comparison statistics following out-of-sample forecasts. These comparison statistics are used in comparing the strength of VAR vis-à-vis PDL in modeling the impacts of advertising expenditures on non-alcoholic beverages.

In the model with PDL, we augmented the AIDS model with polynomial distributed lags of advertising variable with endpoint restrictions (both head and tail restrictions). We used quarterly seasonal dummies to handle possible seasonality in data. Model was estimated using a generalized least squares approach correcting for serial correlation of the disturbance term.

Estimated AIDS model with polynomial distributed lags of the advertising expenditure and quarterly seasonality effects are shown below:

$$(1) \qquad w_{it} = \alpha_i + \sum_{j=1}^{n} \gamma_{ij} lnp_{jt} + \beta_i ln\left[\frac{m}{f(P)}\right] + \sum_{j=1}^{3} d_j\, Q_{ijt} + \sum_{j=1}^{n} \sum_{k=0}^{k} \theta_{ijk} lnA_{jt-k} + e_{it}$$

where $p_{jt}$is the real price of non-alcoholic beverage, m is the real total expenditure, $f(P)$ is the Stone's price index; $f(P) = \sum_{i=1}^{n} w_i lnp_i$, $Q_{ijt}$is the quarterly dummy variable, e_{it} is the additive disturbance term, A_{jt-k} is the polynomial distributed lag version of advertising expenditure. Notice that k is the lag length, $k = 0,1,2, \dots, k$. The new coefficient associated with the polynomial distributed lag advertising expenditure variable is θ_{ijk}. We assume that θ_{ijk} can be represented with a polynomial of degree m, where $m = 0,1,2, \dots, m$.

(2) $$\theta_{ijk} = \varphi_0 + \varphi_1 k + \varphi_2 k^2 + \varphi_3 k^3 + \cdots + \varphi_k k^m$$

According to Sims (1980), one may consider a demand model as multiple economic time series, where lags (to be determined from the data and *a priori* knowledge) of each variable are allowed (in the most general case) to affect the current position of each series. A general statement of the resulting model is given as a vector autoregressive representation (VAR):

(3) $$x_t = \sum_{k=1}^{K} \alpha(k) x_{t-k} + \delta_t$$

where α(k) is an autoregressive matrix of dimension (nxn) at lag k which connects x_t and x_{t-k} and δ_t is a vector residual term of dimension *(nx1)*. In terms of the equations of the VAR, many, indeed most, of the autoregressive parameters α(k) are equal to zero and K is the maximum lag, found through loss function search procedures. Moving all terms involving x_t and x_{t-k} to the left-hand-side of the VAR and writing lags in terms of the lag operator (B), we get the autoregressive representation as:

(4) $$\left(1 - \propto (B)\right) X_t = \delta_t$$

Merely inverting the autoregressive representation gives us the standard moving average representation:

(5) $$X_t = \left(1 - \propto (B)\right)^{-1} \delta_t$$

Written in more discernable terms as an infinite sum gives:

(6) $$X_t = \delta_t + \pi(1)\delta_{t-1} + \pi(2)\delta_{t-2} + \pi(3)\delta_{t-3} + \pi(4)\delta_{t-4} + \cdots$$

In equation (6), the $\pi(i)$ are moving average parameter matrices of dimension *(nxn)* derived from the VAR equation and δ_{t-i} are vectors of historical shocks of dimension *(nx1)*. The structure of the VAR equation allows us to decompose the X vector at t into its historical components. For any particular element of x_t, say element i, we can write it as:

$$(7) \qquad x_{it} = \delta_{it} + \sum_{j=1}^{n} \pi_{ij}(1)\,\delta_{jt-1} + \sum_{j=1}^{n} \pi_{ij}(2)\,\delta_{jt-2} + \ldots$$

Where δ_{jt-k} is the shock in series j in period t-k and $\pi_{ij}(k)$ is the i,j element of the π matrix of the moving average parameter matrix, which gives the response of series i to the shock in period t-k in series x_j. At any time t we can accumulate that portion of the series which is "due to" past shocks in any of the particular series (j) of the vector time-series.

Historical decompositions of time-series models are not independent of the ordering of contemporaneous correlation. In this analysis, the “causal flows” in contemporaneous time will be investigated following the directed graph procedures of Spirtes, Glymour, and Scheines (2000) and Swanson and Granger (1997). Such methods allow the use of a nonrecursive ordering of contemporaneous correlation, which avoids much of the criticism leveled on VAR work with the standard Choleski factorization (Cooley and LeRoy, 1985). In particular, the historical decompositions as well as the impulse response functions will allow an examination of the movement in consumption of non-alcoholic beverages due to historical shocks in potential demand drivers. Depending on the co-integration of the respective variables in the analysis, we will entertain the development and estimation of error-correction models (Johansen and Juselius, 1990; Engle and Granger, 1987).

Data

Initially, monthly household purchases of non-alcoholic beverages (expenditure and quantity information) are generated for each household in the Nielsen Homescan Panel data over the period January 1998 to December 2009. Next, the expenditure and quantity data are summed over all households for each month for each of the aforementioned non-alcoholic beverage categories. As such, we generate monthly purchase data to arrive at a total of 144 observations for each non-alcoholic beverage category. Quantity data are standardized in terms of gallons per person per month and expenditure data are expressed in terms of inflation adjusted dollars. Then taking the ratio of real expenditure to volume, we generate unit values (or real prices) for each non-alcoholic beverage category for each month. To lend support to this approach, we find strong correlations of our data on an annual basis with annual USDA Economic Research Service disappearance data for similar beverage categories. Even though we lose household demographic information with this aggregation, we do not encounter data censoring problems inherent in trying to use micro-level data in estimating demand systems. Advertising expenditure data, obtained from Leading National Advertisers, Inc. and *AdView,* an advertising tracking program maintained by Nielsen, are merged with the time-series data generated through the use of the Nielsen HomeScan panels.

Results and Discussion

Once the VAR and PDL (through augmenting the AIDS model) are estimated, we can ascertain own- and cross-advertising effects of various beverages. Impulse response functions gleaned from the use of the VAR approach would show us the impacts of advertising expenditures of various beverages to a one-time-only shock. The direction and the strength of the impulse would speak to the effect of the adverting expenditure of one beverage on others. Error variance decompositions help us determine the magnitude of the contribution of advertising expenditures of several beverages on a given beverage. Similarly, own- and cross-adverting expenditure elasticities generated through the PDL help us determine the negative and positive spillover effects of advertising expenditure of one beverage on several others. The contemporaneous causal structure pertaining to advertising expenditures, quantities and prices of various beverages help identify endogenous, exogenous and/or weakly exogenous factors. Ultimately, the better model to ascertain the effect of advertising expenditures of various non-alcoholic beverages is identified through the study of out-of-sample forecasts generated though both models. As well, we are in a position to make a comparison of our respective estimates of advertising elasticities with those in the extant literature.

References

American Beverage Association, 2011 (online access on January 2, 2012).

Bessler, D.A. & Akleman, D.G. “Farm Prices, Retail Prices, and Directed Graphs: Results for Pork and Beef.” *American Journal of Agricultural Economics* 80, 5 (1998): 1144.

Beverage Marketing Corporation, 2011, “The Multiple Beverage Marketplace in the U.S.”

Cooley, T. and S. LeRoy. “Atheoretical Macroeconomics: A Critique,” *Journal of Monetary Economics* 16 (1985): 283-308.

Engle, R.F. and C.W.J. Granger.Co-integration and Error Correction: Representation, Estimation, and Testing”, *Econometrica*, 55 (1987):251-276.

Gao, X.M., and J. Lee, “A Factor Analysis Approach to Measure the Biased Effects of Retail Fruit Juice Advertising.” *Empirical Economics* 20(1) (1995):93-107

Johansen, S. and K. Juselius. “Maximum Likelihood Estimation and Inference on Cointegration with Application to the Demand for Money,” *Oxford Bulletin of Economics and Statistics*, 52(1990): 169-210.

Kaiser, H. M. and J.C. Reberte., “Impact of Generic Advertising of Fluid Milk on Demand for Whole, Low-fat, and Skim Milks”, *Journal of Dairy Science*, 79 (1996): 2284-2291.

Kinnucan, H. and O.D. Forker., “Seasonality in the Consumer Response to Milk Advertising with Implications for Milk Promotion Policy”, *American Journal of Agricultural Economics*, 68(3), (1998): 562-571.

Kinnucan, H.W., Y. Miao, H. Xiao, and H.M. Kaiser, “Effects of Advertising on U.S. Non-Alcoholic Beverage Demand: Evidence from A Two-Stage Rotterdam Model.” In M.R. Baye and J.P. Nelson, eds., *Advances in Applied Microeconomics* Amsterdam, Elsevier Science

Sims, C. “Macroeconomics and Reality,” *Econometrica* 48(1980): 1-48.

Spirtes, P., C.N. Glymour, and R. Scheines. *Causation, Prediction, and Search,* The MIT Press, 2000.

Swanson, N. and C.W.J. Granger. “Impulse Response Functions Based on a Causal Approach to Residual Orthogonalization in Vector Autoregressions,” *Journal of the American Statistical Association* 92(1997): 357-67.

Swanson, N.R., and C.W.J. Granger, C.W.J. “Impulse Response Functions Based on a Causal Approach to Residual Orthogonalization in Vector Autoregressions.” *Journal of the American Statistical Association* 92, 437 (1997): 357-367.

Zheng, Y., and H. M. Kaiser., “Advertising and U.S Non-alcoholic Beverage Demand”, *Agricultural and Resource Economics Review”* 37(2), (October 2008): 147-159.