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Estimating Asymmetric Advertising Response: An Application to U.S. Nonalcoholic Beverage Demand

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We propose a regime-switching model that allows demand to respond asymmetrically to upward and downward advertising changes. With the introduction of a smooth transition function, the model features smooth rather than abrupt parameter changes between regimes. We apply the model to nonalcoholic beverage data in the United States for 1974 through 2005 to investigate asymmetric advertising response. Results indicate that a decrease in milk advertising had a more profound impact on milk demand than an increase did. An increase in milk advertising had no impact on milk demand, but a decrease could have an own-advertising elasticity up to 0.049.

Key Words: asymmetric advertising response, demand system, negative asymmetry, nonalcoholic beverage demand, positive asymmetry, regime switching, smooth transition function

JEL Classifications: C32, M37, Q11

A number of researchers have argued that consumers respond asymmetrically to changes in advertising (Hanssens, Parsons, and Schults, pp. 43, 183; Little; Parsons; Vande Kamp and Kaiser 1999). Asymmetric advertising response (AAR) occurs when the magnitude of demand response to a change in advertising differs depending on whether the change is of one sign or another. The conventional wisdom on AAR is that consumers respond more fully to an increase in advertising than to a decrease because of carry-over effect. That is, consumers are immediately impacted by new or increased advertising, but once the advertising is reduced or eliminated, consumers are slow to forget it. This phenomenon was termed "hysteresis" by Little in the marketing literature.

The literature on asymmetric price transmission denotes it as "positive asymmetry" when retail prices respond more fully and quickly to an increase in farm prices than to a decrease (Meyer and v. Cramon-Taubadel; Peltzman). Following such convenience, we define hysteresis as positive AAR in this paper. Alternatively, negative AAR is defined if consumers respond more fully to a decrease in advertising than to an increase.[1] Aykac, Corstjens, and Gautschi found the existence of negative AAR for some small cigarette brands

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[1] A negative AAR does not necessarily mean that the advertising parameter for decreasing advertising is negative.

in the United States, which they referred to as the "small brand condition." These brands are in the small brand condition because they cannot profitably increase their advertising expenditure, but once they reduce their advertising, their market shares will decline. Another explanation for negative AAR is that the satiation effect might be at work. If the market for a commodity is saturated, then advertising's ability to enhance demand will be attenuated because of the limited consumption potential for the good.

Whether demand response to advertising displays positive, negative, or no asymmetry has important implications for optimal advertising policy. Vande Kamp and Kaiser (2000) showed that in the presence of short-run positive AAR, pulsed advertising policies for generic milk advertising in New York City are significantly more effective in raising demand than a uniform (i.e., constant) advertising policy. They showed that with the same advertising budget, milk demand under a pulsed advertising policy was 4.3–6.2% higher than that under a uniform advertising policy. Alternatively, in the case of the small brand condition, which is an extreme case of negative AAR, maintaining advertising at the status quo level would be optimal because an increase in advertising does not help increase market shares but a decrease hurts.[2]

Wolffram's data-splitting approach was widely used in empirical investigation of asymmetry issues. Let A_t^I and A_t^D represent the sum of all period-to-period increases and decreases in advertising in period t, respectively. AAR can be investigated by positing the following linear demand response function:

$$(1) \quad q_t = \beta_0 + \beta_I A_t^I + \beta_D A_t^D + v_t,$$

where t indexes period, β are parameters to be estimated, other demand factors such as prices and income are suppressed, and v is the error term. In Equation (1) demand is a linear function of cumulative increases and cumulative decreases in advertising. Rejection of the null hypothesis in the following hypothesis therefore provides evidence of AAR:

$$(2) \quad \begin{aligned} H_N &: \beta_I = \beta_D \\ H_A &: \beta_I \neq \beta_D. \end{aligned}$$

If $\beta_I > \beta_D$ ($\beta_I < \beta_D$), then positive (negative) AAR is found. Wolffram's approach was further refined to operate more clearly by excluding the impact of the first observation (Houck), to allow lags in the exogenous variables (Ward), and to allow short-run AAR with long-run symmetry assumed (Vande Kamp and Kaiser 1999).

As discussed in detail in the later model section, since all the aforementioned Wolffram based models used a unit step function (dummy variable) to generate the A_t^I and A_t^D series, the models are characterized with an abrupt parameter change from one regime to the other. In some cases it may not seem reasonable to assume the transition is sharp, especially for some aggregated data. As Teräsvirta noted in his widely cited paper on the smooth transition autoregressive models, "Even if one assumes the agents make only dichotomous decisions or change their behavior discretely, it is unlikely that they do this simultaneously. Thus if only an aggregated process is observed, then the regime changes in that process may be more accurately described as being smooth rather than discrete" (p. 217). Hence, in the case of studying AAR where only aggregated advertising data such as industry-level advertising are available, it would be of interest and sometimes more appropriate to use a smooth transition model that allows the advertising response parameters to change slowly.

The objective of this study is twofold. The first is to augment the versatility of Wolffram's approach by allowing the advertising response parameters to change smoothly

[2] This claim holds under the assumption that the total benefit-cost ratio of advertising is greater than one. In other words, if advertising decreases and such decrease causes more loss (due to demand decrease) to the advertiser than the saving from the reduction in advertising, such decrease should be avoided.

along with the value of advertising. This objective is achieved by replacing the unit step function with a smooth continuous function to produce more practical and consistent estimates. The second is to investigate AAR in a system framework using the above proposed data-splitting approach. In an Almost Ideal Demand System (AIDS model) for the demand for nonalcoholic beverages in the United States, each beverage demand is allowed to respond asymmetrically to its upward and downward advertising changes. If AAR is found, the parameter change from β_I to β_D is gradual rather than abrupt.

The second objective is motivated by our observation that no study has investigated the coefficient variation of advertising in an integrated-demand system framework. The assumption of invariant demand response to advertising was relaxed in the literature to allow the advertising parameter to have some trend over time or to be a function of specific variables (Chung and Kaiser; Kinnucan and Forker; Kinnucan and Venkateswaran; Reberte et al.; Schmit and Kaiser), or to allow advertising effectiveness to depend on the advertising intensity (i.e., threshold effect, Adachi and Liu), or to allow the existence of short-run AAR (Vande Kamp and Kaiser 1999). However, these studies all used single-equation models of demand. To our knowledge no study has allowed advertising parameters to vary in a demand system. Modeling advertising in an integrated system framework has the advantage of obtaining a full measure of the advertising impact and therefore not overstating the returns to advertising (Kinnucan and Zheng). We extend the earlier literature on the evaluation of advertising effectiveness by making it possible to test for AAR in a system framework. Nonalcoholic beverages are a promising group for the AAR test since research by Kinnucan et al. firmly rejected the hypothesis that nonalcoholic beverage advertising has no effect on the level of demand for the individual beverages. Since annual time-series data are used in this paper, any AAR found therefore is long term.[3] In the following sections we present the model, discuss the data, estimation procedures, and results, and conclude.

An Econometric Model of Advertising Asymmetry

Introduction of a Smooth Transition Function

Wolffram used the following unit step function ϕ_t to generate the A_t^I and A_t^D used in Equation (1):

$$(3)\quad \phi_t = \begin{cases} 1 & \text{if } A_t - A_{t-1} > 0 \\ 0 & \text{otherwise} \end{cases}$$

$$(4)\quad A_t^I = \begin{cases} A_1 & t = 1 \\ A_1 + \sum_{l=0}^{t-2} \phi_{t-l}\Delta A_{t-l} & \text{for } t = 2, 3, \ldots, T \end{cases}$$

$$(5)\quad A_t^D = \begin{cases} A_1 & t = 1 \\ A_1 + \sum_{l=0}^{t-2} (1-\phi_{t-l})\Delta A_{t-l} & \text{for } t = 2, 3, \ldots, T, \end{cases}$$

where t and l index period, superscripts I and D index the two regimes with increases and decreases in advertising, and $\Delta A_t = A_t - A_{t-1}$. The parameter change from β_I to β_D in Equation (1) is abrupt. If ϕ_t is a smooth continuous function of A_t, the parameter change from β_I to β_D will be smooth along the value of A_t (Enders, pp. 400–402). In other words, the advertising coefficient in period t not only depends on whether A_t increases or decreases from A_{t-1}, but also depends on how far A_t deviates away from A_{t-1}. To achieve this end, the ϕ_t in Equation (3) is replaced by a

[3] Clarke concluded that "90% of the cumulative effect of advertising on sales of mature, frequently purchased, low-price products occurs within 3 to 9 months of the advertising" (p. 355). Therefore, using annual data, on one hand, has an advantage that lag structures need not be specified. On the other hand, the advertising effect (elasticity) found is an implicitly long-term effect. Any AAR found in this paper is long term. Given monthly data (e.g., Vande Kamp and Kaiser 1999, 2000), interested readers can specify lag structure and therefore test if short-term AAR exists using our model. More technical discussion on short-term AAR is available in Vande Kamp and Kaiser (1999).

continuous approximation ϕ'_t using the cumulative logistic integral:

$$(6) \quad \phi'_t = \frac{1}{1 + \exp[-k(A_t - A_{t-1})]}, \quad k > 0,$$

where k is called the smoothness parameter. The ϕ'_t term is used to divide A_t into two series as follows:

$$(7) \quad A_t^I = \begin{cases} A_1 & t=1 \\ A_1 + \sum_{l=0}^{t-2} \max\{\phi'_{t-l}\Delta A_{t-l}, 0\} & \text{for } t = 2, 3, \ldots, T \end{cases}$$

$$(8) \quad A_t^D = \begin{cases} A_1 & t=1 \\ A_1 + \sum_{l=0}^{t-2} \min\{(1 - \phi'_{t-l})\Delta A_{t-l}, 0\} & \text{for } t = 2, 3, \ldots, T. \end{cases}$$

Equation (6) is called a smooth transition function in the econometric literature. Therefore, if A_t exceeds A_{t-1} large enough, ϕ'_t approaches one. In the limit, as k approaches positive infinity, Equation (6) in effect is identical to Equation (3), Equation (7) is identical to Equation (4), and Equation (8) is identical to Equation (5). Another commonly used continuous approximation is the normal function.

Table 1 presents a comparison of several data-splitting approaches—Tweeten and Quance's approach, Wolffram's approach, and the smooth transition version approach proposed in this paper—using data on annual generic milk advertising in the United States. Ten years of data are used for illustration purpose.

The variable ln A_t is the logarithm of milk advertising (in million dollars) from 1974 through 1983.[4] Tweeten and Quance's and Wolffram's approaches all use a unit step function to split the data; the former considers the direct impact of period-to-period variation in ln A_t, and the latter considers the impact of cumulative variation in ln A_t (Manera and Frey). In Wolffram's approach, Equations (3)–(5) are used to split the data. In the smooth-transition-function approach, Equations (6)–(8) are used, with the smoothness parameter (k) in Equation (6) taking the value of one for illustration purpose. Our results using the smooth transition function are directly comparable with Wolffram's. As Table 1 shows, $\ln A_t^I$ $(\ln A_t^D)$ under the heading of "smooth transition function" is smaller than (larger than) or equal to its counterpart under "Wolffram" because the replacement of Equation (3) with Equation (6) smoothes the cumulative variation in ln A_t.

The LA/AIDS Model

A linear approximate AIDS model with a first-order autoregression (AR [1] process) is selected to test for AAR. The AR (1) AIDS model, which uses the smooth transition function to split own advertising into two series in each equation, is posited as follows:

$$(9) \quad \begin{aligned} w_{it} = {} & a_i + b_i \ln(Y_t/P_t) + \sum\nolimits_{j=1}^{5} c_{ij} \ln p_{jt} \\ & + e_{ii}^I \ln A_{it}^I + e_{ii}^D \ln A_{it}^D + \sum\nolimits_{j=1, j \neq i}^{5} e_{ij} \ln A_{jt} \\ & + f_i \ln Age5_t + g_i \ln Fafh_t + \varepsilon_{it} \end{aligned}$$

$$(10) \quad \phi_{it}^* = \frac{1}{1 + \exp[-k(\ln A_{it} - \ln A_{i,t-1})]}, \quad k > 0$$

$$(11) \quad \ln A_{it}^I = \begin{cases} \ln A_{i1} & t=1 \\ \ln A_{i1} + \sum_{l=0}^{t-2} \max\left\{\phi_{i,t-l}^* \Delta \ln A_{i,t-l}, 0\right\} & \text{for } t = 2,3,\ldots,32 \end{cases}$$

$$(12) \quad \ln A_{it}^D = \begin{cases} \ln A_{i1} & t=1 \\ \ln A_{i1} + \sum_{l=0}^{t-2} \min\left\{\left(1 - \phi_{i,t-l}^*\right) \Delta \ln A_{i,t-l}, 0\right\} & \text{for } t = 2,3,\ldots,32 \end{cases}$$

$$(13) \quad \varepsilon_{it} = \rho_i \varepsilon_{i,t-1} + u_{it}.$$

Subscript i (=1, 2, 3, 4, 5) in Equations (9)–(13) indexes the five beverage categories in the nonalcoholic group in order as fluid milk, juice, soft drinks, bottled water, and coffee/tea; t and l index year; p_{jt}, q_{jt}, and A_{jt} are the nominal price, per capita consumption, and real advertising expenditures of item j in year

[4] Wolffram noted that "the transformation of data into logarithms should be done before the variables are split" (p. 358).

Table 1. A Comparison of Data-Splitting Approaches Using Milk Advertising Data

			Unit Step Function					Smooth Transition Function		
			Tweeten and Quance		Wolffram			Logistic (with $k = 1$)		
Year	$\ln A_t$	$\Delta \ln A_t$	$\ln A_t^I$	$\ln A_t^D$	ϕ_t	$\ln A_t^I$	$\ln A_t^D$	ϕ'_t	$\ln A_t^I$	$\ln A_t^D$
1974	4.40	—	4.40	4.40	—	4.40	4.40	—	4.40	4.40
1975	4.28	−0.12	0	4.28	0	4.40	4.28	0.47	4.40	4.33
1976	4.27	−0.01	0	4.27	0	4.40	4.27	0.50	4.40	4.33
1977	4.20	−0.07	0	4.20	0	4.40	4.20	0.48	4.40	4.29
1978	4.19	−0.01	0	4.19	0	4.40	4.19	0.50	4.40	4.29
1979	4.61	0.42	4.61	0	1	4.81	4.19	0.60	4.65	4.29
1980	4.37	−0.24	0	4.37	0	4.81	3.95	0.44	4.65	4.16
1981	3.99	−0.38	0	3.99	0	4.81	3.57	0.41	4.65	3.93
1982	3.45	−0.53	0	3.45	0	4.81	3.03	0.37	4.65	3.59
1983	3.57	0.12	3.57	0	1	4.93	3.03	0.53	4.71	3.59

t; $Y_t = \sum_{i=1}^{5} p_{it}q_{it}$ is the nominal group expenditure in year t; w_{it} is the (conditional) budget share of item i in year t where $w_{it} = p_{it}q_{it}/Y_t$; P_t, $Age5_t$, and $Fafh_t$ are the Stone's geometric price index ($\ln P_t = \sum_{i=1}^{5} w_{it} \ln p_{it}$), the proportion of the U.S. population less than five years of age, and food-away-from-home expenditures as a proportion of food expenditures in year t; superscripts I and D index two regimes in which $\ln A_{it}$ goes up and down, respectively; a, b, c, e, f, and g are the parameters to be estimated in Equation (9); k in Equation (10) is the smoothness parameter to be estimated as well; ρ_i is the first-order autoregressive parameter; and u_{it} is a white noise disturbance. Introduction of the smooth transition function entails nonlinear estimation. By restricting k to be equal across equations and using the LA/AIDS model instead of the nonlinear AIDS model, the computational complexity of the estimation is greatly simplified, and the model easily converges.[5]

In the demand system developed above, each beverage's own-advertising parameter is allowed to vary according to whether its own–advertising change is of one sign or another. The terms $\phi_{it}^{*}e_{ii}^{I}$ and $\left(1-\phi_{it}^{*}\right)e_{ii}^{D}$ in effect represent from year $t-1$ to t, the effects of increases and decreases in beverage i's advertising on its own demand. The term $\phi_{it}^{*}e_{ii}^{I}$ approaches e_{ii}^{I} if the increase in advertising from year $t-1$ to t is large enough so that ϕ_{it}^{*} approaches one. Similarly, $\left(1-\phi_{it}^{*}\right)e_{ii}^{D}$ approaches e_{ii}^{D} if advertising decreases large enough (i.e., ϕ_{it}^{*} approaches zero). The hypothesis of symmetric advertising response for beverage i therefore reduces to a test of $e_{ii}^{I} = e_{ii}^{D}$ which is to be conducted in the following sections.

Data Source and Description

Annual time-series data for the United States for 1974 through 2005 are used for this study. Less aggregated data such as state-level panel data or quarterly data were not available.[6] The price and quantity data were obtained from two government sources: the *CPI Detailed Report* from the U.S. Bureau of Labor Statistics (the price of bottled water was

[5] We tried the model that allows k to be different across equations and the model did not converge. Also note $\ln A_{it} - \ln A_{it-1}$ in Equation (10) does not need to be standardized because it is a growth rate.

[6] Quarterly data were available for price, advertising, *Age5*, and *Fafh* but were not available for consumption.

obtained from Beverage Marketing Corporation) and the *Food Availability (Per Capita) Data System* from the Economic Research Service (ERS) at the U.S. Department of Agriculture. Soft drinks and juice refer specifically to carbonated soft drinks and fruit juice. Data on *Age5* and *Fafh* were obtained from ERS as well. The advertising data were obtained from private sources, chiefly *Ad $ Summary* published by Leading National Advertisers, Inc., and *AdView*, an advertising tracking program at AC Nielsen. Milk advertising in this case was strictly generic advertising. Brand advertising for milk was not available for the 1970s and early 1980s. Juice advertising combined generic and brand advertising. Advertising for the other three beverages categories was all brand advertising. A media cost index (2004 = 100), which was computed from annual changes in promotion and advertising costs by media and provided by Dairy Management Inc., was used to deflate the advertising figures. Demand for bottled water, unlike demand for the other beverage groups, is a relatively recent phenomenon. In 1968 Vittel launched the first plastic bottle aimed at general public consumption (American Beverage Association).[7] Yearly per capita consumption of bottled water was only around two gallons in the late 1970s. No data were available regarding bottled-water price prior to 1984 and bottled-water advertising expenditures prior to 1985, so we use imputation method to compensate for the missing data. For example, observable bottled-water prices are regressed on the other four beverage prices and advertising (with an R^2 of 0.96), and then the equation is used to generate water prices for the period where water prices are unobservable. The prediction equation for bottled-water advertising includes the other four beverage advertising, gross domestic product (GDP), and food-away-from-home and food-at-home expenditures (with an R^2 of 0.81). Definitions of variables and summary statistics for the data are reported in Table 2. Of the 32 years, the number of years with increase in (real) advertising is 13, 20, 16, 14, and 16 for the five beverages, respectively, providing two balanced regimes for each beverage.[8]

Estimation and Results

The model satisfies the multivariate normality assumption and a Hausman-Wu endogeneity test indicates little evidence of endogeneity for the real group expenditure. The endogeneity is examined using $\ln(Inc_t/P_t)$, log of real GDP, and a linear trend variable as instruments for $\ln(Y_t/P_t)$ where *Inc* is per capita personal income obtained from the U.S. Bureau of Economic Analysis. That is, first regress $\ln(Y_t/P_t)$ on $\ln(Inc_t/P_t)$, log(GDP), and the trend. The residuals saved from the above regression enter each equation of the demand system as an additional explanatory variable. The Wald statistic for the null hypothesis that the coefficients for the residuals are jointly zero is not statistically significant at the 5% level. We select the AR (1) specification since the Godfrey's serial autocorrelation test indicates so.

Since treating the imputed missing data as if they were true observations (also known as single imputation) generally leads to underestimated variances for parameters (Rubin 1996; Rubin and Schenker; Shao and Sitter), we follow Rubin (1987) to use multiple imputation method to account for the underestimation in the variance. That is, we repeat drawing from the two prediction equations to fill the missing data *m* times. The *m* complete data sets are used to fit the AIDS model to obtain *m* repeated parameter estimates and covariances. Finally, the *m* repeated parameter estimates and covariances are combined to produce valid inferential results. We conduct the above three steps using the PROC MI, PROC MODEL, and PROC MIANALYZE procedures in SAS 9.1, respectively. Typically, as few as five or three

[7] Source: http://www.ameribev.org/all-about-beverage-products-manufacturing-marketing-consumption/americas-beverage-products/bottled-drinking/history/index.aspx.

[8] Such calculation does not include the imputed portion of advertising for bottled water.

Table 2. Variable Definitions and Summary Statistics, 1974–2005

Variable	Definition	Mean	Minimum	Maximum	Std. Dev.
q_1	Per capita fluid milk consumption, gallons/person	25.35	20.98	29.50	2.54
q_2	Per capita juice consumption, gallons/person	7.91	6.15	9.10	0.84
q_3	Per capita soft-drink consumption, gallons/person	43.98	27.60	53.80	8.41
q_4	Per capita bottled-water consumption, gallons/person	9.41	1.26	25.43	6.99
q_5	Per capita coffee/tea consumption, gallons/person	33.37	28.16	40.62	2.72
p_1	Nominal retail price for fluid milk, \$/gallon	2.16	1.23	3.34	0.61
p_2	Nominal retail price for juice, \$/gallon	3.67	1.50	5.26	1.16
p_3	Nominal retail price for soft drinks, \$/gallon	1.66	0.83	2.11	0.35
p_4	Nominal retail price for bottled water, \$/gallon	1.08	0.73	1.36	0.17
p_5	Nominal retail price for coffee/tea, \$/gallon	0.84	0.33	1.12	0.20
A_1	Advertising expenditures for fluid milk, million \$ in 2004 \$	56.06	9.77	160.57	42.81
A_2	Advertising expenditures for juice, million \$ in 2004 \$	244.12	31.33	730.42	148.34
A_3	Advertising expenditures for soft drinks, million \$ in 2004 \$	422.78	97.00	807.77	197.77
A_4	Advertising expenditures for bottled water, million \$ in 2004 \$	56.99	17.07	157.23	36.64
A_5	Advertising expenditures for coffee/tea, million \$ in 2004 \$	215.71	73.86	340.45	61.49
w_1	Budget share for fluid milk, conditional	0.28	0.23	0.44	0.05
w_2	Budget share for juice, conditional	0.15	0.11	0.17	0.02
w_3	Budget share for soft drinks, conditional	0.37	0.28	0.42	0.04
w_4	Budget share for bottled water, conditional	0.05	0.01	0.12	0.03
w_5	Budget share for coffee/tea, conditional	0.15	0.11	0.23	0.03
Fafh (%)	Food-away-from-home expenditures/total food expenditures	43.45	34.10	48.49	4.16
Age5 (%)	Proportion of the U.S. population younger than age five	7.25	6.78	7.71	0.29

multiple imputations are necessary (Rubin 1996, p. 480). We set $m = 20$ in this paper to err on the safe side. Results are robust for alternative values for m (e.g., $m = 10$ and $m = 30$) in that when the alternative values for m are used, estimated parameters and standard errors change slightly only at the three-digit level.

The AIDS model is estimated using the using the full information maximum likelihood method (FIML) with 160 effective observations (five equations and 32 years). Price homogeneity and symmetry and adding up are treated as maintained hypotheses (i.e., $\sum_{j=1}^{5} c_{ij} = 0$, $c_{ij} = c_{ji}$, $\sum_{i=1}^{5} b_i = \sum_{i=1}^{5} f_i = \sum_{i=1}^{5} g_i = 0$, and $\sum_{i=1}^{5} a_i = 1$). All equations share a common autoregressive parameter. If all advertising variables (own and cross) had been split and entered as regressors for each equation (resulting in a total of 10 advertising variables for each equation), the system is perfectly singular. In our case only the own advertising variable is split, therefore all the five equations are used.[9] Table 3 presents the parameter estimates of the model.

Columns (1)–(5) show that nine of the 15 price coefficients, including four own-price coefficients are statistically significant at the 5% level (default), and two other cross-price coefficients are statistically significant at the 10% level (denoted as weakly significant). Columns (7)–(10) show that about one-half of the expenditure, *Age5*, and *Fafh* parameters are statistically significant or weakly signifi-

[9] An example where all equations are used in an imperfectly singular demand system is Moschini and Vissa.

cant, and the adjusted R^2 are high.[10] Our key interests here lie in the own-advertising parameters in columns (12)–(21), where each beverage has four estimated cross-advertising parameters and two estimated own-advertising parameters—one for the regime with increases in advertising and the other for the regime with decreases in advertising. For example, fluid milk's own-advertising parameters are 0.002 (not statistically significant) for its upward advertising changes and 0.012 (statistically significant) for its downward advertising changes. That is a typical example of negative AAR. On the contrary, the advertising parameters for bottled water are 0.010 (weakly significant) and −0.005 (not statistically significant), respectively, for upward and downward changes in its advertising. The own-advertising parameters for the other three beverages are not statistically significant.

For comparison purpose, we reestimate the system with symmetric advertising response and report the results in Table 4. Three of the own-advertising parameters are weakly significant; they are 0.006 for milk, 0.024 for soft drinks, and 0.012 for coffee/tea. Other estimated parameters in Table 4 are comparable with those in Table 3. For example, coffee/tea advertising is found to increase milk demand with a cross-advertising parameter of 0.028 in Table 4 and 0.017 in Table 3. Both parameters are statistically significant.

To err on the safe side, we restrict our test of AAR to those beverages that have statistically significant or weakly significant own-advertising parameters in both specifications, that is, milk. A t-test is performed for milk to test the null hypothesis of $e^{I}_{11} = e^{D}_{11}$. The resulting test statistic is 2.55 (p-value = 0.048), which indicates rejection of symmetry. That is, the difference between the two own-advertising parameters for milk is statistically significant. In summary, we found that milk demand overall was positively related to milk advertising. However, a decrease in milk advertising had a more profound impact on milk demand than an increase did, displaying evidence of negative AAR. Such a result may signal a saturated market for milk. The result can also be reconciled in the perspective of consumption trends in the U.S. nonalcoholic beverages. Previous studies (e.g., Kinnucan et al.) documented a negative trend in milk and coffee/tea (per capita) consumption and a positive trend in soft-drink consumption.[11] Bottled-water consumption has been trending up at a much faster speed than soft drinks' because of its rising popularity. Over the period we addressed in this study (1974–2005), the changes of budget shares for the five beverages are 0.44 to 0.24 for milk, 0.11 to 0.15 for juice, 0.28 to 0.37 for soft drinks, 0.01 to 0.12 for bottled water, and 0.16 to 0.12 for coffee/tea. The above numbers show that milk gave up market shares notably to bottled water and soft drinks. In a competition for market share, milk might be in a defensive position because of its negative consumption trend, so that its advertising increases did not matter to demand, but its advertising decreases did.

Based on the information in Tables 3 and 4, compensated own-price and cross-price elasticities (E^{C}_{ii} and E^{C}_{ij}), uncompensated own-price elasticities (E^{U}_{ii}), expenditure elasticities (E_i), and own-advertising elasticities (α_{ii}) are computed as $E^{C}_{ii} = -1 + c_{ii}/w_i + w_i$, $E^{C}_{ij} = c_{ij}/w_i + w_j$, $E^{U}_{ii} = -1 + c_{ii}/w_i - b_i$, $E_i = 1 + b_i/w_i$, and $\alpha_{ii} = e_{ii}/w_i$, where w_i is the market share for beverage i in 2005. Results are shown in Table 5.

For E^{C}_{ii}, double asterisks (single asterisk) indicate that c_{ii} is statistically significant at the 5% (10%) level. Similar denotation applies to other elasticities except E^{U}_{ii}. Because E^{U}_{ii} involves two parameters, its standard errors are derived using the Delta method. Double asterisks for E^{U}_{ii} mean that $-1 + c_{ii}/w_i - b_i$ is statistically significant.

Both models in Table 5 indicate that all the own-price elasticities, compensated and uncompensated, are inelastic and have the

[10] The causes of large standard error estimate of k in Table 3 are purely numerical, as noted by van Dijk, Teräsvirta, and Franses (p. 21).

[11] Bottled water was not included in the study by Kinnucan et al.

Table 3. Parameter Estimates of Conditional Demand Equations Where Asymmetric Advertising Response Is Allowed

	Price Coefficients					Intercept	Expend.	*Age5*	*Fafh*		
Equations	c_{i1} (1)	c_{i2} (2)	c_{i3} (3)	c_{i4} (4)	c_{i5} (5)	a_i (6)	b_i (7)	f_i (8)	g_i (9)	Adj. R^2 (10)	k (11)
Milk	0.182**					1.288**	−0.090*	0.103**	−0.229**	0.99	92.197
	(0.021)					(0.255)	(0.043)	(0.034)	(0.052)		(5932.380)
Juice	−0.063**	0.088**				0.271	−0.061	−0.134*	0.115	0.82	
	(0.022)	(0.038)				(0.409)	(0.082)	(0.073)	(0.087)		
Soft drinks	−0.111**	0.021	0.147**			−1.201**	0.004	0.199**	0.289**	0.98	
	(0.021)	(0.024)	(0.031)			(0.261)	(0.058)	(0.048)	(0.053)		
Bottled water	0.050**	−0.040*	−0.045**	0.045		−0.188	−0.015	−0.019	0.085	0.98	
	(0.013)	(0.019)	(0.017)	(0.024)		(0.301)	(0.046)	(0.045)	(0.060)		
Coffee/tea	−0.058**	−0.009	−0.015*	−0.010	0.092**	0.830**	0.162**	−0.150**	−0.259**	0.97	
	(0.008)	(0.012)	(0.009)	(0.010)	(0.009)	(0.241)	(0.058)	(0.053)	(0.049)		

	Advertising Coefficients									
Equations	e^I_{i1} (12)	e^D_{i1} (13)	e^I_{i2} (14)	e^D_{i2} (15)	e^I_{i3} (16)	e^D_{i3} (17)	e^I_{i4} (18)	e^D_{i4} (19)	e^I_{i5} (20)	e^D_{i5} (21)
Milk	0.002 (0.005)	0.012** (0.005)	0.003 (0.006)		−0.018* (0.010)		0.002 (0.003)		0.017** (0.006)	
Juice	0.001 (0.005)		−0.008 (0.012)	0.004 (0.012)	0.016 (0.016)		−0.008 (0.005)		−0.020* (0.010)	
Soft drinks	0.001 (0.004)		−0.013** (0.006)		0.013 (0.009)	−0.009 (0.011)	0.0004 (0.003)		0.014** (0.006)	
Bottled water	−0.005 (0.003)		0.012* (0.006)		0.002 (0.011)		0.010* (0.005)	−0.005 (0.004)	−0.010 (0.007)	
Coffee/tea	−0.001 (0.003)		0.002 (0.006)		−0.00002 (0.011)		0.004 (0.003)		−0.019 (0.011)	0.005 (0.006)

** and * denote estimates are significant at the 5% and 10% levels, respectively. Asymptotic standard errors are in parentheses. The first-order autoregressive parameter is −0.064 (not statistically significant). For cross-advertising parameters, $e^I_{ij}=e^D_{ij}=e_{ij}$ holds for $i \neq j$.

Table 4. Parameter Estimates of Conditional Demand Equations with Symmetric Advertising Response

	Price Coefficients					Intercept	Expend.	*Age5*	*Fafh*	
	c_{i1}	c_{i2}	c_{i3}	c_{i4}	c_{i5}	a_i	b_i	f_i	g_i	Adj. R^2
Equations	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Milk	0.160**					1.569**	−0.050	0.076*	−0.330**	0.99
	(0.027)					(0.290)	(0.056)	(0.041)	(0.049)	
Juice	−0.065**	0.093*				0.371	−0.061	−0.119*	0.076	0.86
	(0.024)	(0.042)				(0.515)	(0.085)	(0.058)	(0.083)	
Soft drinks	−0.098**	0.021	0.149**			−1.205**	−0.040	0.138**	0.377**	0.97
	(0.031)	(0.024)	(0.044)			(0.306)	(0.069)	(0.053)	(0.059)	
Bottled water	0.072**	−0.037	−0.065**	0.035		−0.401	−0.088	−0.063	0.252**	0.96
	(0.016)	(0.025)	(0.023)	(0.026)		(0.309)	(0.064)	(0.046)	(0.064)	
Coffee/tea	−0.069**	−0.012	−0.007	−0.005	0.093**	0.666**	0.240**	−0.032	−0.375**	0.96
	(0.012)	(0.013)	(0.014)	(0.011)	(0.013)	(0.254)	(0.068)	(0.050)	(0.049)	

	Advertising Coefficients				
	e_{i1}	e_{i2}	e_{i3}	e_{i4}	e_{i5}
Equations	(11)	(12)	(13)	(14)	(15)
Milk	0.006* (0.003)	0.010* (0.006)	−0.035** (0.012)	0.003 (0.003)	0.028** (0.007)
Juice	0.0002 (0.005)	−0.002 (0.009)	0.008 (0.015)	−0.009** (0.004)	−0.012 (0.009)
Soft drinks	0.003 (0.004)	−0.021** (0.007)	0.024* (0.014)	−0.001 (0.004)	0.001 (0.008)
Bottled water	−0.004 (0.004)	0.006 (0.007)	0.031** (0.012)	0.003 (0.003)	−0.029** (0.006)
Coffee/Tea	−0.006 (0.003)	0.007 (0.007)	−0.028** (0.012)	0.004 (0.003)	0.012* (0.006)

** and * denote estimates are significant at the 5% and 10% levels, respectively. Asymptotic standard errors are in parentheses. The first-order autoregressive parameter is −0.193 (not statistically significant).

Table 5. Elasticities

Quantity of	Compensated Price Elasticities E_{i1}^C	E_{i2}^C	E_{i3}^C	E_{i4}^C	E_{i5}^C	Own-Advertising Elasticities α_{ii}^I	α_{ii}^D	Expend. Elasticities E_i	Uncompensated Price Elasticities E_{ii}^U
Results with Asymmetric Advertising Response									
Milk	−0.003**	−0.109**	−0.091**	0.322**	−0.120**	0.009	0.049**	0.626*	−0.153**
Juice	−0.172**	−0.269**	0.529	−0.146*	0.059	−0.053	0.025	0.595	−0.360**
Soft drinks	−0.059**	0.210	−0.233**	−0.004**	0.080*	0.034	−0.023	1.010	−0.609**
Bottled water	0.668**	−0.192*	−0.014**	−0.495	0.033	0.083*	−0.042	0.871	−0.596
Coffee/tea	−0.238**	0.074	0.247*	0.032	−0.114**	−0.158	0.039	2.345**	−0.397**
Results with Symmetric Advertising Response									
Milk	−0.094**	−0.117**	−0.036**	0.414**	−0.166**	0.024*		0.791	−0.284**
Juice	−0.185**	−0.235*	0.507	−0.127	0.040	−0.014		0.596	−0.326*
Soft drinks	−0.023**	0.207	−0.227**	−0.060**	0.103	0.064*		0.891	−0.558**
Bottled water	0.858**	−0.167	−0.191**	−0.578	0.078	0.028		0.236	−0.605
Coffee/tea	−0.330**	0.051	0.316	0.075	−0.112**	0.102*		2.992**	−0.473**

** and * denote estimates are significant at the 5% and 10% level, respectively. Standard errors for E_{ii}^U are obtained using the Delta method.

correct sign. Soft drinks are the most price elastic beverages within the group in terms of uncompensated elasticities. Coffee/tea is found the most expenditure elastic with an elasticity of 2.345 for the model allowing for AAR and 2.992 for the model with symmetry. The model allowing for AAR shows that the own-advertising elasticity for milk is 0.009 (not statistically significant) for an increase in advertising and 0.049 (statistically significant) for a decrease in advertising. The interpretation is, the advertising elasticity for a large decrease in milk advertising approaches 0.049. For a small/moderate decrease, the advertising elasticity falls in the range of (0, 0.049).

Conclusion

In this study we first develop a regime-switching model that allows demand to respond asymmetrically to upward and downward advertising changes. AAR is then investigated for the U.S. nonalcoholic beverages in a system framework using the above developed model. Our results indicate existence of negative AAR. For milk the estimated own-advertising parameter corresponding to an advertising decrease is found larger than that corresponding to an advertising increase. That is, an increase in milk advertising has no impact on milk demand, but a decrease can have an own-advertising elasticity up to 0.049, depending on the size of advertising decrease. The satiation effect and negative consumption trend may cause negative AAR for milk.

We acknowledge one limitation of this study is the use of annual data with limited degrees of freedom, which only allows to test for long-term AAR and makes strategic policy implications harder to obtain than using monthly or quarterly data. Efforts are being made to make up for this limitation. In addition, although making use of the linear AIDS model reduces the computational complexity significantly, the usual caveats regarding the linear AIDS model apply (e.g., Alston, Chalfant, and Piggott; Moschini). The main contribution of this paper lies in that the model features smooth parameter changes between regimes and allows testing for AAR in a system framework. To our knowledge, this is a first attempt to model and test for AAR in an integrated framework.

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