The Impact of Generic Advertising on Household Cheese Purchases: A Censored Autocorrelated Regression Approach

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Generic promotion of dairy products supported by assessments on dairy farm operators and fluid milk processors has become a familiar phenomena as shown by the widely recognized “Milk Mustache”, “Got Milk” and “Power of Cheese” advertising campaigns. These programs have been the subject of considerable analysis in terms of their overall effectiveness and have typically been found to generate positive net effects (Forker and Kinnucan, 1991; Sun, Blisard, and Blaylock, 1995; Van de Kamp and Kaiser, 1999). These evaluations have tended to focus on aggregate market impacts (e.g. Blaylock and Blisard, 1988, 1990; Lenz, Kaiser, and Chung, 1998; Sun, Blisard and Blaylock, 1995; Blisard, et. al. 1999). These analyses have found positive net impacts on dairy product utilization with benefit-cost ratios (i.e. the ratio of the advertising-enhanced producer revenue increases to advertising cost) in the range of 1.5:1 to 6.5:1. These time series analyses have used commercial disappearance data as a measure of dairy product utilization. This measure includes the direct use of a particular dairy product as well as its use as a food ingredient and its purchase in restaurants. In contrast, little work has been done at the household level with a focus on at-home consumption.

The policy and legal environment surrounding these programs is changing. With a more market-oriented dairy policy, the importance of both advertising and non-advertising promotion efforts in maintaining industry revenues is increasing. Recent Federal District and Supreme Court decisions have concluded that some generic promotion programs based on mandatory industry assessments have been declared unconstitutional (Ellliot, 2001; Crespi and Sexton, 2001). These decisions imply that program evaluations are likely to become more important as they are used as justification for program continuation.

In this paper, a model is developed and applied to household panel data on biweekly cheese purchases (1997-99) to examine the impact of generic cheese advertising on at-home consumption. The model is unique in that it not only allows for the use of simulated probability techniques to solve high-order integrals, but also partitions the data into smaller components to allow for analysis of longer time periods, increased accuracy, and reduced computing time. The empirical results of this study are useful in providing additional insight as to how generic cheese advertising impact various households’ cheese purchase behavior.

Background and Previous Research

For the present analysis we extend the analysis of Dong et al. (2001) by adopting an alternative estimation procedure that allows for analysis of longer time periods. Specifically, the dynamic Tobit structure used above requires evaluation of probability integrals with dimensions equal to the number of nonpurchase occasions over the entire survey period. As the length of the household panel increases estimation is more questionable due to lower speed and decreased numerical accuracy. The approach adopted here allows for evaluation of integrals within "censored strings" of the panel, resulting in an increase in the length of time series for which a censored model can be estimated by reducing the dimension of integration. This results in reduced estimation time and increases estimation accuracy.

The impact of the promotion of branded foods has been well investigated (e.g., Aliawadi and Neslin, 1998; Chiang, 1991). A comprehensive analysis typically hypothesizes impacts on both purchase quantity and timing (Neslin, Hendersen, and Quelch, 1985; Gupta, 1988,1991). In contrast to the analysis of branded promotion, little research has been done on the effect of generic advertising on household-level purchases, largely due to lack of data.[1] We can address the question as to whether generic dairy product promotion impacts demand via the use of household panel data. For this analysis we examine household purchases of cheese over 1997-2000 using information on biweekly purchases by U.S. household panel. Given sporadic purchase patterns we account for both the panel nature of the data and censored purchases in our analysis.

Recent studies have attempted to quantify household dairy product purchase characteristics. Dong and Gould (2000) use a U.S. household panel over a 13-week period to examine the dynamics of the discrete decision to purchase cheese. In their analysis an AR(1) error structure is incorporated within a probit model. Given the large number of dimensions over which the probability integral to be evaluated, simulated maximum likelihood methods based on the GHK algorithm were used (Hajivassilou, 1994; Hajivassilou, McFadden and Ruud, 1996). They found significant persistent household heterogeneity that was not eliminated by the inclusion of lagged exogenous variables. Unfortunately, the authors limited their analysis to the decision whether or not to purchase and did not include branded or generic promotion information.

Dong et al. (2001) use a similar simulated maximum likelihood method to estimate parameters of a dynamic Tobit model of U.S. household fluid milk purchases. Using the same AR(1) error structure as in Dong and Gould (2000), they account for both state dependence and household heterogeneity. The authors include a measure of generic advertising and found that this advertising increased purchase quantity and decreased inter-purchase time.

Gould (1997) used event history analysis to examine the discrete cheese purchase decisions by a 170-week panel of U.S. households. The dependent variable in that analysis was interpurchase time. A number of alternative interpurchase time distribution assumptions were tested and the impact of a variety of household and purchase characteristics on purchase timing investigated. One of the exogenous variables included in the analysis was coupon utilization. Likelihood ratio tests rejected the null hypothesis that coupon use has no impact on cheese purchase timing. Unfortunately, no information representing other promotional variables were included and given the nature of event history analysis the author could not examine purchase quantity decisions.

Description of Econometric Model

For this analysis we examine U.S. at-home cheese demand. We follow a biweekly panel of U.S. households for the years 1997-1999 (i.e., 78 biweekly periods). Using their purchase history we apply the theoretical model suggested by Zeger and Brookmeyer (1986) to account for censored bi-weekly cheese purchases while at the same time allowing for an autocorrelated error structure.

Assume we have a panel of *N* households observed over *T* periods. For the i^{th} household y_{it} is a *T x 1* vector of observed biweekly cheese purchases. We represent the relationship between latent cheese purchases, y_{it}^0, and a *T x K* matrix of exogenous market, household, and advertising variables, x_{it} via the following:

(1) $y_{it}^0 = x_{it} b + e_{it} \quad (i = 1, \ldots, N) \; (t = 1, \ldots, T)$

where b is a (K x 1) vector of unknown regression coefficients. Given we are examining biweekly cheese purchases there is significant censoring. We represent this censoring process via the following:

$$(2)\quad y_{it} = \begin{cases} y_{it}^{0}, & \text{if } e_{it} > -x_{it} b \\ 0\,, & \text{otherwise} \end{cases} \quad (i = 1,\ldots, N)\ \ (t = 1,\ldots, T)$$

To complete the model specification we need to specify the relationship of the above error terms across households and over time. The conventional approach would be to restrict the error variance-covariance matrix, Ω, to be household and time invariant. That is:

$$(3)\quad \Omega_i = \Omega = E\left(u_{it}\, u_{it}^{'}\right) = s^{2} I_T,\ \forall i \quad (i = 1,\ldots, N) \quad (t = 1,\ldots,T)$$

where s^{2} is an estimated variance parameter and I_T is a T-dimensional identity matrix. This structure yields a pooled cross-sectional Tobit model that ignores temporal and spatial linkages. The parameters of this model can be estimated using traditional maximum likelihood procedures.

We relax this assumption and allow for household specific heterogeneity and state dependence. Assume the error term e_{it} consists of two components:

$$(4)\quad e_{it} = a_i + n_{it} \quad (1 = 1,\ldots, N)\ \ (t = 1,\ldots T)$$

where a_i is uncorrelated with n_{it} and can be interpreted as a household-specific normal random variable used to capture household heterogeneity. Ignoring state dependence, one can assume that n_{it} is an *iid* normal random variable. State dependence is an empirical question and a test for its existence can be quantified via the adoption of a particular autoregressive error structure.

For this analysis we assume that n_{it} follows a first-order autoregressive process (AR(1)). Specifically, for this one-factor plus AR(1) error structure, we assume:

$$(5)\quad n_{it} = r\ n_{it-1} + e_{it}\ ;\ |\,r\,| < 1 \quad (1 = 1,\ldots, N)\ \ (t = 1,\ldots T)\,,$$

where r is the autocorrelation coefficient and $e_{it} \sim \mathrm{N}\left(0\,, s_1^{2}\right)$ for all i and t. Additionally, $a_i \sim \mathrm{N}\left(0\,, s_2^{2}\right)$ for all i and persists over time.[2]

Incorporating (4) and (5) implies the covariance matrix, Ω, becomes:

$$(6)\quad \Omega = s_2^2 1_T + s_1^2 \begin{bmatrix} 1 & r & r^2 & r^3 & \cdots & r^{T-2} & r^{T-1} \\ r & 1 & r & r^2 & \cdots & r^{T-3} & r^{T-2} \\ r^2 & r & 1 & r & \cdots & r^{T-4} & r^{T-3} \\ . & . & . & . & \cdots & . & . \\ . & . & . & . & \cdots & . & . \\ . & . & . & . & \cdots & . & . \\ r^{T-1} & r^{T-2} & r^{T-3} & r^{T-4} & \cdots & r & 1 \end{bmatrix}$$

where 1_T is a T x T matrix of one's.[3]

With the above error structure Zeger and Brookmeyer (1986) show that to develop density of y_t, conditioned on all past observations, one simply needs to incorporate information on the previous *p* consecutive uncensored observations, where *p* is the order of the autoregressive process (p.722-723). In our AR(1) structure, this conditional density can be represented as:

$$(7)\quad f(y_{it} \mid y_{i,t-1}, y_{i,t-2}, \ldots, y_{i,0}) =$$
$$f(y_{i,t} \mid y_{i,t-1}, y_{i,t-2}, \ldots, y_{i,t-C_{t_i}}, y_{i,t-C_{t_i}-1}) \quad (i = 1, \ldots, N)\ (t = 1, \ldots, T)$$

where the previous C_t observations are censored and $y_{i,t-Ct-1}$ is uncensored.

Given (7), the likelihood of a censored AR(1) process can be represented by two distinct components. The first component consists of the product of the conditional probability density function (pdf) calculated for each uncensored observation that is immediately preceded by an uncensored value (e.g., y_t, y_{t-1} are both uncensored). Let U be the set containing those uncensored observations for which the preceding value (*p*=1) is also uncensored. The second likelihood function component quantifies the contribution of censored observations and uncensored observations for which the preceding value is censored (Zeger and Brookmeyer, 1986).

Figure 1 provides an example of how we partition a purchase history to develop its likelihood function. With the assumed AR(1) process and given (7) we define a censored string (Y_j, j=1,…,J) as starting with the first censored observation after a purchase period and ending after a purchase.[4] In the simple example shown in this figure, there are three censored strings. The first censored string (Y_1) starts in period 3 and ends with the purchase in period 6. The second censored string (Y_2) lasts for two periods after beginning in period 7. The last censored string (Y_3) starts in period 10 and ends in period 12. Note that each censored string consists of v_j^C censored (Y_j^C) and one uncensored value (Y_j^U). That is, Y_j is composed of v_j^C+1 periods and is preceded by an uncensored value, Z_j, which may be the ending uncensored observation in the previous censored string or an observation in the set U.

With the first observation in the series is uncensored, Zeger and Brookmeyer (1986) show the combined likelihood function for all observations for a particular household is:

$$(8)\quad l(b,\Omega,q \mid y) = l_U l_C = \prod_{t\in U} f(y_t \mid y_{t-1}) \prod_{j=1}^{J} f\left(Y_j^U \mid Z_j\right) F_j\left(Y_j^C \mid Z_j, Y_j^U\right)$$

where J is the number of censored strings, $F_j(Y_j^C|Z_j, Y_j^U)$ is the conditional cumulative distribution function (CDF) of the censored values (Y_j^C) conditional on the preceding uncensored value (Z_j) and the uncensored observation in the j^{th} censored string (Y_j^U), and:

$$(9)\quad F_j\left(Y_j^C \mid Z_j, Y_j^U\right) = \int_{-\infty}^{0} f\left(Y_j^C \mid Z_j, Y_j^U\right) dY_j^C \quad (j=1,\ldots,\mathrm{J})$$

where the upper and lower limits of integration are of dimension v_j^C. From (8) and (9) the uncensored portion of a censored string makes a contribution to the likelihood function conditional on the most recent preceding uncensored observation, while the censored portion contributes conditionally on the surrounding uncensored values (Zeger and Brookmeyer, 1986 p.723).

We can use the sequence of purchases shown in Figure 1 to develop the likelihood function for the first 12 time periods. The component of the likelihood function associated with the uncensored observations in set U is:

$$(10)\quad l_U = f(y_2 \mid y_1) \bullet f(y_9 \mid y_8)$$

and the censored strings' contribution to the likelihood function is:

$$(11)\quad l_C = f(y_6 \mid y_2) \int_{-\infty}^{0}\int_{-\infty}^{0}\int_{-\infty}^{0} f(y_3, y_4, y_5 \mid y_2, y_6)\, dy_3\, dy_4\, dy_5\; f(y_8 \mid y_6) \int_{-\infty}^{0} f(y_7 \mid y_6, y_8)\, dy_7$$
$$f(y_{12} \mid y_9) \int_{-\infty}^{0}\int_{-\infty}^{0} f(y_{10}, y_{11} \mid y_9, y_{12})\, dy_{10}\, dy_{11}$$

Thus to generalize the above, for a particular household we segment the history of purchase/non-purchase periods into uncensored and censored strings according to the methods outlined above and in Zeger and Brookmeyer (1986). With J censored strings for this household and in each censored string we have v_j^C censored observations, each censored string has $T_j=v_j^C+1$ observations. Applying the error structure defined in (6), we can write the associated variance-covariance matrix of the error terms for the j[th] censored string as:

$$\text{(12)}\quad \Sigma_j = \sigma_2^2 1_{T_j} + \sigma_1^2 \begin{bmatrix} 1 & \rho & \rho^2 & \cdots & \rho^{T_j-1} \\ \rho & 1 & \rho & \cdots & \rho^{T_j-2} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ \rho^{T_j-1} & \rho^{T_j-2} & \rho^{T_j-3} & \cdots & 1 \end{bmatrix} \quad j=(1,\ldots,J),$$

where Σ_j is a sub-matrix of the full covariance matrix, Ω.

We evaluate expressions for the mean and variance of censored and uncensored observations using our latent variable definition. For convenience, consider the following series: $y_0 > 0$, $y_1 = y_2 = \ldots = y_t = \ldots = y_{Tj-1} = 0$, $y_{Tj} > 0, \ldots, y_{s-1} > 0$, $y_s > 0, \ldots$. For those observations in set U, the expected value (μ_s) and variance ($V(y_s|y_{s-1})$) are respectively:

$$\text{(13)}\quad \mu_s = E(y_s|y_{s-1}) = X_s\beta + E(\varepsilon_s \mid \varepsilon_{s-1}) = X_s\beta + \left(\frac{\sigma_2^2 + \rho\sigma_1^2}{\sigma_2^2+\sigma_1^2}\right)(y_{s-1} - X_{s-1}\beta)$$

$$\mathrm{V}(y_s|y_{s-1}) = \mathrm{V}(\varepsilon_s|\varepsilon_{s-1}) = (\sigma_2^2+\sigma_1^2) - \frac{(\sigma_2^2+\rho\sigma_1^2)^2}{(\sigma_2^2+\sigma_1^2)}, \quad \text{and} \quad s \in U.$$

Similarly, although now conditioned not on the previous observation, but on the previous uncensored observation, the expected value (η_j^U) and variance (Σ_j^u) for the uncensored observation in the j[th] censored string can be expressed as:

$$\text{(14)}\quad \eta_j^U = E(Y_j^U|Z_j) = E(y_{T_j}|y_0) = X_{T_j}\beta + E(\varepsilon_{Tj}|\varepsilon_0) = X_{T_j}\beta + \left[\frac{\sigma_2^2+\sigma_1^2\rho^{T_j}}{\sigma_2^2+\sigma_1^2}\right](y_0 - X_0\beta)$$

and

$$\Sigma_j^u = \mathrm{cov}(Y_j^U|Z_j) = V(y_{Tj}|y_0) = V(\varepsilon_{T_j}|\varepsilon_0) = (\sigma_2^2+\sigma_1^2) - \frac{(\sigma_2^2+\sigma_1^2\rho^{T_j})^2}{(\sigma_2^2+\sigma_1^2)}.$$

For the censored observations within the censored string first define $Y^C=(y_1, y_2,\ldots,y_{Tj-1})'$, $X^C\beta=(X_1\beta, X_2\beta, \ldots, X_{Tj-1}\beta)'$, $E^C=(\varepsilon_1, \varepsilon_2, \ldots, \varepsilon_{Tj-1})'$, $Y^U=(y_0, y_{Tj})'$, and $E^U=(\varepsilon_0, \varepsilon_{Tj})'$. Now for the censored observations within the censored string it can be shown that:

$$(15)\quad h_j^C = E\left(Y_j^C \middle| Z_j, Y_j^U\right) = E\left(Y^C \middle| Y^U\right) = X^C b + E\left(E^C \middle| E^U\right) = X^C b + \Sigma_{CU}\left(\Sigma_{UU}\right)^{-1} E^U$$

and

$$\Sigma_j^C = \operatorname{cov}\left(Y_j^C \middle| Z_j, Y_j^U\right) = V\left(Y^C \middle| Y^U\right) = V\left(E^C \middle| E^U\right) = \Sigma_{CC} - \Sigma_{CU}\left(\Sigma_{UU}\right)^{-1}\left(\Sigma_{CU}\right)'$$

$$\text{where}\quad \Sigma_{CU} = \begin{bmatrix} s_2^2 + s_1^2 r & s_2^2 + s_1^2 r^{T_j-1} \\ s_2^2 + s_1^2 r^2 & s_2^2 + s_1^2 r^{T_j-2} \\ \vdots & \vdots \\ s_2^2 + s_1^2 r^{T_j-2} & s_2^2 + s_1^2 r^2 \\ s_2^2 + s_1^2 r^{T_j-1} & s_2^2 + s_1^2 r \end{bmatrix},\quad \Sigma_{UU} = \begin{bmatrix} s_2^2 + s_1^2 & s_2^2 + s_1^2 r^{T_j} \\ s_2^2 + s_1^2 r^{T_j} & s_2^2 + s_1^2 \end{bmatrix},$$

$$\text{and}\quad \Sigma_{CC} = \begin{bmatrix} s_2^2 + s_1^2 & s_2^2 + s_1^2 r & \cdots & s_2^2 + s_1^2 r^{T_j-3} & s_2^2 + s_1^2 r^{T_j-2} \\ s_2^2 + s_1^2 r & s_2^2 + s_1^2 & \cdots & s_2^2 + s_1^2 r^{T_j-4} & s_2^2 + s_1^2 r^{T_j-3} \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ s_2^2 + s_1^2 r^{T_j-3} & s_2^2 + s_1^2 r^{T_j-4} & \cdots & s_2^2 + s_1^2 & s_2^2 + s_1^2 r \\ s_2^2 + s_1^2 r^{T_j-2} & s_2^2 + s_1^2 r^{T_j-3} & \cdots & s_2^2 + s_1^2 r & s_2^2 + s_1^2 \end{bmatrix}.$$

Given the above definitions, the likelihood function shown in (8) is:

$$(16)\quad \mathrm{l}(b, \Omega \mid \mathrm{y}) = \prod_{t \in U} f_1\left(\frac{\mathrm{y_t} - m_\mathrm{t}}{\mathrm{V}\left(\mathrm{y_s} \middle| y_{s-1}\right)}\right) \prod_{j=1}^{J} f_j\left[\left(\Sigma_j^U\right)^{-1}\left(\mathrm{Y}_j^U - h_j^U\right)\right] \Phi_j\left[\left(\Sigma_j^C\right)^{-1}\left(-h_j^U\right)\right]$$

where $f_t(\bullet)$ is a standard normal PDF and $\Phi_t(\bullet)$ is the standard normal CDF of dimension t.

With $\sum_j$ defined in (12) and means and variances defined in (13)-(15), the likelihood function above requires the evaluation of T_j-fold integrals determined by the length of the individual household censored strings. When T_j exceeds 3 or 4, the evaluation of these multi-dimensional integrals becomes difficult. Similar to Dong et al. (2001), we use a simulated probability method to evaluate these integrals. However, the advantage with this model is that the total length of the simulation period is equal to the length of the specific household censored string, rather than the total number of household censored observations.

Recently, several probability simulators have been introduced and investigated in literature (Breslaw, 1994; Geweke, Keane and Runkle, 1997). The smooth recursive conditioning simulator (GHK) was used here because this algorithm is the most reliable simulator of those examined by Hajivassiliou, McFadden and Rudd (1996).

The censored regression model with error structure depicted in (6) can be used to generate predictions of conditional and unconditional values of purchases for a particular time period. Given time period *t*, the expected conditional purchase by the ith household can be evaluated using the following:

$$(17)\quad \mathrm{E}\left(\mathrm{y}_{\mathrm{it}} \mid \mathrm{y}_{\mathrm{it}} > 0\right) = \mathrm{x}_{\mathrm{it}} b + \sqrt{s_1^2 + s_2^2}\,\frac{f(q_{\mathrm{it}})}{\Phi(q_{\mathrm{it}})}$$

where $q = \frac{x_{it} b}{\sqrt{s_1^2 + s_2^2}}$, and $Prob\left(y_{it} > 0\right) = \Phi\left(q_{it}\right)$. Similar to traditional Tobit models, unconditional expected purchases equal the product of purchase probability and the above conditional purchase amounts:

$$(18)\quad E\left(y_{it}\right) = Prob\left(y_{it} > 0\right) \cdot E\left(y_{it} \mid y_{it} > 0\right) = \Phi\left(q_{it}\right)\mathrm{x}_{\mathrm{it}} b + \sqrt{s_1^2 + s_2^2} \cdot f\left(q_{it}\right)$$

From (18) we can decompose the unconditional purchase elasticities into two components: conditional purchase and purchase probability (McDonald and Moffit, 1980).

With the panel nature of the data used in this analysis and the assumed AR-1 error structure, we expand the traditional Tobit analysis by examining the impact of previous purchase patterns on conditional and unconditional expected purchase quantities. For example suppose in period t-1, the ith household did not purchase cheese. Following Rosenbaum (1961), the tth period's expected purchase quantity can be shown to be:

$$(19)\quad E\left(y_{it} \mid y_{it-1} = 0\right) = Prob\left(y_{it} > 0 \mid y_{it-1} = 0\right) E\left(y_{it} \mid y_{it} > 0, y_{it-1} = 0\right),$$

where $Prob\left(y_{it} > 0 \mid y_{it-1} = 0\right) = 1 - \frac{\Phi_2\left(-q_{it}, -q_{it-1}, d\right)}{\Phi\left(-q_{it-1}\right)}$, and

$$E(y_{it} \mid y_{it} > 0, y_{it-1} = 0) = x_{it} b + \sqrt{s_1^2 + s_2^2}\,\frac{f(q_{it})\Phi\left(\frac{-q_{it-1} - d q_{it}}{\sqrt{1-d^2}}\right) + d f(q_{it-1})\Phi\left(\frac{q_{it} + d q_{it-1}}{\sqrt{1-d^2}}\right)}{\Phi_2(q_{it}, -q_{it-1}, d)},$$

where $\Phi_2\left(-q_{it}, -q_{it-1}, d\right)$ represents the standard joint (bivariate) normal cdf of y_{it} and y_{it-1} with correlation coefficient $d = \frac{s_1^2 r + s_2^2}{s_1^2 + s_2^2}$.

The above provides a framework for evaluating the t^{th} period's purchase quantity given no purchases in the previous period. In contrast, given a purchase occasion during t-1, we have,

(20) $E(y_{it} \mid y_{it-1} > 0) = Prob\left(y_{it} > 0 \mid y_{it-1} > 0\right) E\left(y_{it} \mid y_{it} > 0, y_{it-1} > 0\right)$,

where $Prob\left(y_{it} > 0 \mid y_{t-1} > 0\right) = 1 - \frac{\Phi\left(-q_{it}\right) - \Phi_2\left(-q_{it}, -q_{it-1}, d\right)}{\Phi\left(q_{it-1}\right)}$, and

$$E\left(y_{it} \mid y_{it} > 0, y_{it-1} > 0\right) = x_{it} b + \sqrt{s_1^2 + s_2^2}\, \frac{f\left(q_{it}\right)\Phi\left(\frac{q_{it-1} - dq_{it}}{\sqrt{1-d^2}}\right) + df\left(q_{it-1}\right)\Phi\left(\frac{q_{it} - dq_{it-1}}{\sqrt{1-d^2}}\right)}{\Phi_2\left(q_{it}, q_{it-1}, d\right)}.$$

The relationships shown in (19) and (20) are determined, in part, by the correlation between current purchase (y_{it}) and previous purchase (y_{it-1}) amounts. If there is no correlation between y_{it} and y_{it-1}, i.e., s_2^2 and r defined above are both zero, the two sets of equations will be the same as that shown in (18) . Similar to (18), elasticities of the expected values in (19) and (20) can be decomposed into the intensive (conditional purchase) and extensive (purchase probability) responses.

Description of the Household Panel Data

The data used in this analysis is based on the ACNielsen Homescan Panel of U.S. households. Households comprising the panel used hand-held scanners to record purchase information including date of purchase, UPC code, total expenditure, and quantities purchased. Given the relative shelf life of most cheeses and time period involved, the purchase occasion data was aggregated to biweekly purchase periods. A random sample of 1088 U.S. households was used for this analysis. The data encompasses the 1997-1999 period. Given the use of biweekly periods, a total of 84,864 observations were contained in the final data set. Purchase information was combined with a set of annual household demographic data collected from panel households.

The Dairy and Tobacco Adjustment Act of 1983 authorized a national program for the promotion, research, and nutritional education of dairy products. This program is funded by a 15-cent-per-hundredweight assessment on farm milk produced for commercial use. The program is administered by Dairy Management Incorporated (DMI) formed in 1995 as a result of the merger between the National Dairy Promotion and Research Board and the United Dairy Industry Association. From DMI we obtained national biweekly generic cheese advertising expenditures financed through the use of these mandatory assessments. Due to a lack of media specific data at the biweekly level, total expenditures on all media types are included in this analysis. Unfortunately this biweekly data was only available for the U.S. as a whole. We did have estimates, however, of annual generic promotion expenditures within each of 75 dominant market areas (DMA's).[5] To more accurately represent the level of advertising effort households face in each DMA, we use the annual DMA expenditure percentages as the weight to partition the national biweekly expenditure data across DMA's. While not a perfect substitute for actual biweekly spending by DMA, the calculated approximation used here provides us with information on the differences in advertising intensity via market expenditures across the U.S.[6]

There is a large amount of literature suggesting that both current and past generic advertising efforts impact current purchase behavior (Forker and Ward, 1993; Ferrero et al., 1996). It is often assumed that these impacts follow a concave time path as in Figure 2. That is, there is an immediate but relatively small initial effect of advertising in current period *t*. Subsequent impacts increase as the consumer has time to process and recall the advertising message (e.g. in time *t*+1, *t*+2, etc.); however, after some time period the effectiveness of this advertising effort starts to decline and reaches zero at time (L+1). Similar to previous generic dairy product research, we model this behavior as a polynomial distributed lag (PDL), with end-point restrictions equal to zero (e.g. Suzuki et al., 1994; Kaiser, 2000). This structure requires an estimate of the slope of the advertising response function. This PDL structure with end-point restrictions can be written as:

$$(21) \quad y_t = a + \sum_{i=0}^{L} b_i ADV_{t-i} + e_t$$

subject to:

$$b_i = l_0 + l_1 i + l_2 i^2$$

$$b_{-1} = b_{L+1} = 0,$$

where L is the total lag length and all other variables are suppressed in a , for notational convenience. After substituting, (21) simplifies to:

$$(22) \quad y_t = a + l_2 ADV_t^* + e_t$$

where,

$$ADV_t^* = \sum_{i=0}^{L} (i^2 - Li - (L+1)) ADV_{t-i} .$$

For our analysis, generic advertising impacts are modeled assuming a 20-biweek (i.e., 9-month) PDL structure.[7] Advertising expenditure data from 1996 were used to provide three full years (1997-1999) of data for estimation. Alternative lag lengths were evaluated based on previous generic advertising studies for dairy products (e.g., Kaiser, 2000; Lenz, Kaiser, and Chung, 1998). The assumed 20-biweek lag length is well within the boundaries established by Clarke (1976) who concluded that 90% of the cumulative effects of advertising for frequently purchased products is captured within three to nine months. In addition, to capture the diminishing-returns aspect of advertising response, advertising expenditures are converted to their square roots.

Prices are not observed directly in the panel data. An estimate of price was obtained by dividing reported expenditures by quantity on each purchase occasion. A number of alternative approaches were considered to obtain estimates of unobserved cheese prices during nonpurchase periods. For this analysis we impute prices for non-purchase biweeks for each household as being equal to the mean DMA price for that biweekly period.[8]

Table 1 provides an overview of household characteristics, as well as the advertising and price variables used in the analysis. Besides household annual pre-tax income (HH_INC), the female head's employment status (FHWORKS), educational attainment (COLLEGE), and age (FHAGE) are used as explanatory variables.[9] We also incorporate measures of household size (HH_SIZE) and member age distribution. Dichotomous regional, race/ethnicity, and monthly variables are included to control for geographic, race-related, and seasonal variations in cheese purchase patterns.

Generic cheese advertising varied considerably both over time and across DMA. National cheese advertising expenditures averaged just under $1.8 million per biweek, with a range of $21,000 to $5 million and had a coefficient of variation (CV) of 0.70 (Figure 3). Average annual expenditures from 1997 through 1999 were approximately $46 million per year.

Cheeses advertising spending proportions across the 75 DMAs were considerably more variable (CV=1.73), ranging from as low as 0.002 in the Lexington DMA to as high as 0.204 in the Los Angeles DMA. Multiplying the annual DMA spending proportions with the biweekly national advertising expenditures resulted in average biweekly DMA cheese advertising expenditures of approximately $21,000, with a high of $740,000 in the Los Angeles DMA during 1997.

The last section of Table 1 provides an overview of the sample household purchase characteristics while Figure 4 shows the distribution of annual per capita cheese purchases. The average per lb. net price (shelf price - coupon value redeemed) was $3.33 and the average amount of purchase per purchase occasion was 1.67 lbs. There is substantial variability in the purchase price and quantity across households. Slightly less than half of the 78 biweekly periods included in this analysis were purchase occasions. Again, there was a wide range in the number of purchase periods per household. Approximately 20% of the households purchase cheese for less than 20 of the biweekly study periods (i.e., 26% of periods) and about 13% of the sample households purchase cheese for more than 60 biweekly periods (i.e.,77% of periods). On a quantity basis, more than one quarter of the households purchase less than 5 pounds per capita annually while 15% purchase more than 15 pounds (Figure 4).

Econometric Results

Parameter estimates were obtained by maximizing the likelihood function in (8) using the GAUSS software system. We use 500 replicates to simulate the multinormal probability in the likelihood function using the GHK procedure outlined by Breslaw (1994). The estimated coefficients are presented in Table 2. All of the estimated coefficients except for the variable associated with the youngest age group composition variable (PER_LT13) were statistically significant.

To examine the statistical significance of the assumed AR(1) structure we use a likelihood ratio to test the null hypothesis that contemporaneous error terms are not correlated (e.g., $r=0$ and $s_2^2=0$). That is, we estimate the traditional Tobit model implied by (2) and (3). The ratio of the resulting likelihood functions of the Tobit model with value obtained using (8) results in a c_2^2 statistic of 4662.9, which clearly results in a rejection of the above null hypothesis.

From (18) and using a similar decomposition of marginal impacts as in McDonald and Moffit (1986), the sign of the marginal impact of a change in an exogenous variable on $E(y_{it})$, $E(y_{it}|y_{it}>0)$, and $Prob(y_{it}>0)$ can be directly interpreted from the estimated coefficients. Given our use of total household purchases, it was not surprising that we obtain a negative coefficient associated with the inverse of the HH_SIZE variable. We also find that household composition is an important determinant of cheese purchases given the statistically significant PER_1317 and PER_GT65 coefficients. The greater the percent of teenage household members, the more purchased. In contrast, the presence of senior adults in the household has a negative effect, *ceterus paribus*, on household purchases.

As the age of meal planner increases, here assumed to be the female household head, household cheese purchases decrease. Relative to households classified as white, minority households were found to have lower biweekly cheese purchases. These are similar to the results of Blaylock and Smallwood (1983), Gould and Lin (1994) and Gould (1992). These lower purchase rates may be reflecting not only cultural differences with respect to food choices but also increased rates of lactose intolerance in non-white populations.

We found significant regional differences in cheese purchases. Compared to households in the Pacific region, households in the other regions exhibited significantly lower conditional and unconditional cheese purchases. These results are in contrast to Gould and Lin (1994) who found little evidence of regional variation. Gould, Cornick and Cox (1994) found that in terms of purchases of full fat natural American cheese the Pacific region exhibited larger household sales. Full fat processed cheeses did not exhibit this relationship.

Sun, Blisard, and Blaylock (1995) use time series (monthly) data to estimated conditional household cheese demand. They found that household demand for natural (cheddar) cheese increased significantly during November and December due to the Thanksgiving and Christmas holidays. In this analysis we use December as our month of comparison. Similar to the their results, the 11 estimated coefficients are all negative indicating increased demand during December. The months of April and July showed the smallest purchase amounts.

The above hypothesis test clearly shows the importance of accounting for correlation associated with serial dependence (via the s_1^2 and r terms) and household heterogeneity (via the s_2^2 term). From these coefficients we can compute the overall correlation between the current purchase at time t and the previous purchase at time t-1, $\delta = \frac{\sigma_1^2 \rho + \sigma_2^2}{\sigma_1^2 + \sigma_2^2}$. Our estimated δ value of 0.1848 implies that lagged purchases are positively related to current purchases. We can decompose this overall effect into its serial state dependence, $\delta_1 = \frac{\sigma_1^2 \rho}{\sigma_1^2 + \sigma_2^2}$, and household heterogeneity effects, $\delta_2 = \frac{\sigma_2^2}{\sigma_1^2 + \sigma_2^2}$. From this decomposition, we find that the positive habit persistence associated with household heterogeneity (δ_2 = 0.2156) outweighs the relatively small negative serial dependence effect (δ_1 = -0.0308). This is similar to the effects found in Dong et al. (2001) in their analysis of fluid milk purchases and has important implications when evaluating short-term price promotions versus long-term household preference shifting effects; e.g. from advertising (Dong et al. 2001). Certainly if advertising results in a change in household behavior, which is then persistent over time (δ_2), then this strategy would be preferred to a short-term price promotion where the effects are relatively small (δ_1) and return to “status quo” after the promotion period has ended.

From the estimated coefficients in Table 2, we evaluated two categories of elasticities. One set does not take into account the purchase history of a household (i.e., equation (17)) and the second set recognizes previous period purchase pattern. We evaluate these elasticities for the 55^{th} biweekly period using explanatory variables mean values (Table 3).[10] The elasticities displayed in columns (1), (3) and (5) are similar to the traditional Tobit-type elasticities that do not account for purchase history. The product of the probability (col. 5) and conditional purchase values (col. 3) equals the unconditional ($E(Y_t)$, col. 1), and the unconditional elasticities are the sum of the conditional (or intensive) and purchase probability (or extensive) elasticities. As is evident in Table 3, the unconditional, or overall, elasticities are largely the result of the extensive purchase probability impacts with more than 62% of the total elasticity response for all the variables is accounted for by the purchase probability impacts (i.e., $Prob(y_t>0)$) .

In terms of the total effect of a change in exogenous variables we find that cheese demand is price inelastic with an estimated unconditional price elasticity of –0.886. This result is similar to previous analyses. Using household-level data for March 1991-March 1992, Gould and Lin (1994) obtain a similar total cheese own-price elasticity estimate of -0.574. Using time series data, Heien and Wessells (1990) obtain an elasticity value of –0.370. Our total cheese elasticity estimate here is between the –1.4 elasticity value for natural cheese and the –0.792 for processed cheese in Sun, Blisard and Blaylock (1995). Our estimated income elasticity is quite low with a value of less than 0.10. This again is similar to previous research results. Gould and Lin(1994) obtain an income elasticity estimate of 0.045. Surprisingly, using monthly data for the U.S. for the Jan. 1982-June 1993 period, Sun, Blisard and Blaylock (1995) did not find a significant income effect on the demand for natural or processed cheeses.

The estimated household size elasticity is reasonable and we find that household composition matters. There appears to be a cohort effect with respect to reduced cheese purchases for households, the older the female (or male) household head and the greater the percentage of household members over the age of 65. Dong and Gould (2000) using a 13-week U.S. household panel estimated a probit model that incorporates a similar AR-1 error structure as used here in an analysis of household cheese purchases. They found that relative to households headed by middle age adults, households headed by senior adults (>65) had a lower probability of cheese purchase. Gould and Lin (1994) also found a negative relationship between total cheese purchases and whether the main meal planner was older than 35 years of age was established. Gould (1992) found evidence of this negative relationship using the BLS Consumer Expenditure Survey.

Given the panel nature of our data set we modify the above elasticity calculations to account for previous household purchases. In columns labeled (2), (4) and (6) we present the unconditional (in terms of current purchases), conditional and probability purchase elasticities for households that did not purchase in the previous period by using (19) and (20) to evaluate expected values, conditional on previous purchases. The predicted value of unconditional purchases given that there was no purchase in the previous period is less than the predicted value without considering such purchases (0.82 vs. 0.87 lbs) and is largely the result of the decrease in the conditional purchase probability. This is likely due to the strong positive correlation of habit persistence mentioned earlier; i.e., compared with the unconditional purchase today given that there was a purchase in the prior period of over one pound..

In terms of the estimated elasticities, there is a striking similarity of elasticities with and without considering previous purchase amounts, where again the differences in the unconditional elasticities is largely the result of differences in the elasticities of purchase probability. The largest absolute differences were obtained with respect to the price elasticity. There was an increase in the probability price elasticity from –0.558 to –0.679. This results in an overall unconditional (on current purchase status) elasticity increase from –0.886 to –0.973.

The expected values and elasticities conditional on their being a purchase occasion in the previous period were omitted from Table 3 due to the conditional purchase estimated value and elasticities were virtually identical to the results shown in this table. [11] The immediate implication of this is simple: once the decision to purchase this period has been made, the prior periods purchase activity has little effect on today's actions. This, however, was not the case for purchase probability. The expected purchase probability given a purchase in the last period was higher than that given no purchase in the prior time period and resulted in lower elasticities for all variables. This again is intuitively sensible; i.e., households that purchased in the prior time period are more persistent buyers of cheese and, as such, are less responsive to changes in market or demographic conditions.

The Impact of Generic Advertising on Cheese Purchases

While the effect of generic advertising was significant in the estimated model (see Table 2), the resulting impacts as represented by long-run elasticities are relatively small (see Table 3). We predict that at the mean values of the exogenous variables, a 1% increase in generic advertising expenditures would result in only a 0.0028% increase in cheese purchases. This level is considerably below the elasticities of the other continuous variables implying that generic advertising has a positive, but relatively small effect on at-home purchases of cheese products.

The long-run advertising elasticity estimated here is below the 0.015 value obtained by Kaiser (2000). This estimate is based on aggregate national quarterly data from 1975-1999 including *total* disappearance of cheese, which includes both at-home and away-from-home consumption. While not directly comparable, if the elasticity reported by Kaiser can be interpreted as a total, or weighted average effect of at-home and away-from-home consumption, then it may be the case that the away-from-home response (e.g. in restaurants, food service, etc.), which comprises a larger market share of total cheese disappearance, is higher than that for at-home consumption.

From the elasticities in Table 3, we also see that the preponderance of the total (unconditional) advertising effect appears to be the result of the purchase probability effect. Two-thirds of the total generic advertising effect originates from a change in the purchase probability. These findings indicate that advertising positively affects both the level of conditional purchases, as well as purchase frequency. The advertising results here are consistent with Sun, Blisard, and Blaylock (1995) and Blisard et al. (1999) who found that generic advertising was successful in inducing people into the natural cheese market, but that it did not influence current consumers. However, for processed cheese, they found both effects to contribute positively to household demand. Our total cheese estimate encompasses both natural and processed cheeses. While a substantial amount of cheese advertising is brand-specific, they found no significant brand effect for natural cheese and combined the generic and brand components in the processed cheese model due to the preponderance of one dominant advertiser in the brand market. Appropriate branded advertising data was not available for this study. While increasing consumption is certainly a goal of any advertising program, branded advertising efforts also heavily concentrate on taking current consumption away from competitors' products. Therefore, it is unlikely that including such information in the model would reverse the conclusions reached here.

As expected, the purchase probability proportion of the total effect increases in the case of no purchase in the prior time period (0.0021/0.0030). While the overall levels of the advertising elasticities are small, this results is at least an encouraging comparison. Specifically, even though the conditional purchase elasticities are identical (col. 3 vs. col. 4, Table 3) implying that the advertising effect on the amount purchased is indifferent to the prior purchase history, advertising seems to be more relatively more effective, at least marginally, at inducing a purchase given a preceding non-purchase occasion.

The recent literature (e.g. Blisard et al., 1999; Kaiser, 2000) has shown generic cheese advertising elasticities below that of their fluid milk counterparts. For example, Kaiser (2000) using aggregate national quarterly data from 1975-1999 estimated long-run generic elasticities of 0.051 for fluid milk and 0.015 for cheese. A relative comparison of these two elasticities show that fluid milk advertising, at the margin, to be about 3.4 times more "effective" than cheese. What, of course, is of most interest to producers is whether these elasticities translate into a sufficient level of demand and price-enhancing response to cover and hopefully exceed the advertising outlay taken from check-off dollars. While the elasticities provide unit-less measures for relative comparison and give us useful insights to responsiveness of these programs at the margin, given the differences in the advertising budgets (fluid milk advertising has been roughly three times that of cheese), a 1% change in generic fluid milk expenditures is a different amount of dollars compared with a 1% change in generic cheese expenditure, and neither elasticity by itself can address the primary interest of producers mentioned above. As a result, most studies of generic promotion effectiveness attempt to calculate benefit-cost ratios of the promotion programs. That is, comparing the change in producer surplus from the advertising program relative to its cost.

Kaiser (2000) estimates an aggregate-level benefit cost ratio of 4.29:1 for the Dairy Program (i.e. including both the producer fluid milk and cheese advertising programs) over the time period of 1996-1999. Similarly, using Kaiser's original model structure, Blisard et al. (1999) estimated gross returns to dairy farmers from September 1984 through September 1997 to be $3.44 for each dollar spent on generic advertising.

It is a difficult task to estimate such a return when starting with household-level purchase data. To fully implement such a simulation procedure, a complex model structure similar to that of Kaiser's would be necessary to account for various price and market transmission relationships. Furthermore, in this analysis we are restricted to at-home consumption effects only, which as mentioned above comprise about 40% of total cheese consumption in the U.S., complicating the evaluation of advertising effectiveness even further. While the estimated advertising response was positive and significant indicating that the generic advertising efforts are effective at increasing the at-home purchases of cheese, the calculated elasticity was relatively small, lending some doubt to the bottom-line benefit-cost ratio for producers from this at-home consumption component.

To quantify this relationship, we apply an equilibrium displacement modeling (EDM) approach to provide some estimate of the overall effectiveness of generic cheese advertising to the at-home consumption of cheese. In short, the EDM approach uses elasticities, baseline prices, and quantities to derive estimates of a change in producer revenues due to a change in generic advertising (Kinnucan, Xiao, and Hsia, 1996; and Kinnucan, 1999). Using the EDM proposed by Kinnucan (1999) and ignoring trade effects, we express the effect of a change in advertising expenditures on industry profits by:

(22) $R_A \equiv \frac{\partial R}{\partial A} = a \Big/ \left(x_Q + x_D \right) - \Gamma$ and $a = \frac{x_A VQ}{A}$,

where *R* is net economic surplus to domestic producers, *A* is domestic advertising expenditures, x_A is the long-run advertising elasticity, V is market price, Q is domestic quantity, x_Q is the domestic supply elasticity, x_D is the absolute value of the domestic demand elasticity, and $\Gamma \equiv \frac{x_D}{t x_Q + x_D}$ represents the proportion of the per unit assessment (*t*) borne by producers with $t = \frac{V}{V - t}$.[12] R_A represents the marginal *net* advertising return, taking into account the cost of advertising (via Γ), as opposed to the marginal *gross* returns estimated by Kaiser (1999) and Blisard et al. (1999).

Table 4 presents the baseline values and parameters necessary for the EDM application. Price and production levels of cheese (in milk fat equivalents) are taken from Kaiser's simulated values from 1996-99 to approximate farm-level revenues allocated to cheese sales. The second component of a, $\frac{VQ}{A}$, represents the advertising intensity of the generic program in relation to the value of farm production. Since it is not possible to partition the advertising expenditures into their at-home and away-from-home components, both the total farm cheese revenues (approximated as the MFE of cheese disappearance multiplied by the average farm milk price) and total advertising expenditures are included in equation (22). To evaluate returns over a range of supply response, we compute net marginal returns using both the short- and long-run supply elasticities from Kaiser (2000), as well as setting x_Q = 0 to provide a measure for which production is fixed. The results of this application are shown in Table 5.

Given the relatively low long-run advertising elasticity for at-home cheese purchases, it is not too surprising that net returns are negative, but modest. Comparing the gross returns (i.e. benefit-cost ratio) with those of Blisard et al. (1999) and Kaiser (2000), it appears the at-home cheese component of total milk product consumption effect to generic advertising is considerably less. Recall that the Blisard et al. (1999) and the Kaiser (2000) estimates represent returns to producers from *both* the fluid milk and cheese programs and that the advertising elasticities for fluid milk were over three times larger than cheese. The losses estimated here are modest and are affected by the combination of the relatively low advertising elasticity and high demand elasticity. For example, using a price elasticity one-half that of the current price elasticity (i.e., x_D=.443), arguably still a relatively large in magnitude response, would result in all net return calculations being positive. The relatively high, but still inelastic total price elasticity here may also be due to quality price-effects discussed earlier and not accounted for in the model.

Basic economic theory tells us that if the objective is to maximize returns to producers, then the level of advertising should be determined at the point where net marginal returns are equal to zero. The results here seem to indicate that the level of cheese advertising is likely near, but somewhat beyond, that optimal point in terms of at-home consumption. This is not to say that overall cheese advertising is showing negative returns, since we are excluding a large component of total U.S. cheese disappearance. However, it does give some indication that the direction of the cheese advertising program to the away-from-home market may be appropriate.

Conclusions

As agriculture in general, and the dairy industry in particular, moves towards a more market-oriented system, understanding the relationships and significance of generic promotion efforts to enhance producer revenues will remain a high-priority concern. This concern has been highlighted more recently by the questioning of the constitutionality of such programs. Evaluation of these programs and understanding the underlying demand relationships is important at both the aggregate and household levels. While considerable work has been accomplished at the aggregate level evaluating the effectiveness of dairy product promotion, relatively little has been done at the household level, to analyze the impact of at-home dairy product consumption. Furthermore, in contrast to the analysis of branded promotion efforts, little research has been done on the effect of generic advertising on household-level purchases, largely due to a lack of available data.

While the benefits of household-level analysis with respect to generic advertising programs is clear, integrating such effects into models using panel type, censored data is more complicated. While the use of panel data has increased considerably in the past few years, solving more complicated censored data models highlights the problem areas of computing time and accuracy. We develop a model here that not only allows for the use of simulated probability techniques to solve high-order integrals, but also partitions the data into smaller components to allow for analysis of longer time periods, increased accuracy, and reduced computing time. The model is applied to household panel data on biweekly cheese purchases from 1996-1999.

Estimation results revealed that price, household income, and household composition are important determinants of cheese demand. The price effect was relatively large but inelastic and the income effect was positive but relatively small. While increasing the proportion of teenagers had a direct effect on household cheese purchases, there was an inverse relationship with people above 65 years of age. The total affect on purchases from changes in these variables was largely the result of extensive purchase probability effects, rather than changes in the conditional purchase levels.

Generic cheese advertising exhibited a positive and significant relationship with household cheese purchases; however the resulting elasticity was relatively small. An application to estimate producer net returns to this component of demand revealed that the advertising program is likely near but somewhat beyond optimal spending levels, as evidenced by small, but modest negative net returns. However, these results are cautioned by the fact that only at-home cheese consumption is considered here, comprising roughly 40% of total cheese disappearance. The net return calculations were also sensitive to the relatively high level of demand elasticities, likely inflated by quality-price effects not controlled for in this model. Subsequent research in this direction will help to solidify such return calculations with the use of household panel data.

Table 1. Overview of Household and Purchase Data Used in the Econometric Model

Variable	Description	Units	Mean
HH_INC	Annual Household Pre-Tax Income	$000	48.1 (33.1)
COLLEGE	Meal Planner Complete College Education	0/1	0.361
FHWORKS	Female Works Outside Home	0/1	0.507
FHAGE	Meal Planner Age	Years	53.0 (13.8)
Household Size/Composition			
HH_SIZE	Number of Household Members	#	2.4 (1.2)
PER_LT13	Per Cent of Household Members < 13 Years	%	7.3 (16.4)
PER_1317	Per Cent of Teenage Household Members	%	3.8 (11.0)
PER_GT65	Per Cent of Senior Household Members	%	24.3 (39.6)
Race/Ethnicity			
BLACK	Female Head Self-Identifies as Black	0/1	0.051
ASIAN	Female Head Self-Identifies as Asian	0/1	0.007
SPANISH	Female Head Self-Identifies as Hispanic	0/1	0.044
Regional Dummy Variables Identifying Household Location			
ENC	East North Central	0/1	0.165
ESC	East South Central	0/1	0.033
MA	Mid-Atlantic	0/1	0.132
MNT	Mountain	0/1	0.105
NE	Northeast	0/1	0.053
SA	South Atlantic	0/1	0.184
WNC	West North Central	0/1	0.081
WSC	West South Central	0/1	0.119
Advertising Expenditures			
ADVP2_20	Polynomial Distributed Lag Stock Variable with End Point Restrictions, 20-biweek Lags	$00 mil.	-20.43 (12.29)
USCHZADV	U.S. Cheese Advertising Expenditures, aggregated across all media types.	$000/bi-week	1769.65 (1236.20)
DMA_PROPN	DMA Annual Spending Proportion	%	1.3 (2.3)
DMACHZADV	DMA Cheese Advertising Expenditures	$000/bi-week	21.00 (45.23)
Purchase Characteristics			
NETPRICE	Conditional Cheese Price Net of Coupon Value	$/lb.	3.326 (0.964)
CHEESEQ	Conditional Cheese Quantity Purchased	Lbs.	1.67 (1.55)
% Purchase Occasions	Percent of Biweeks With Cheese Purchases	%	48.6 (23.1)

Note: Monthly dummy variables (M1-M12) are also included in the model to account for seasonality.

Table 2. Coefficients Obtained From Estimating the Censored Autocorrelated Model

Variable	Coefficient	Std. Error	Variable	Coefficient	Std. Error
Intercept	2.9634	0.0572	ADVP2_20	-0.0010	0.0003
ln(NETPRICE)	-1.5060	0.0086	Monthly Dummy Variables		
ln(HH_INC)	0.1604	0.0067	January	-0.2730	0.0399
COLLEGE	-0.0454	0.0086	February	-0.4330	0.0475
FHWORKS	-0.0958	0.0096	March	-0.4257	0.0488
FHAGE	-0.0025	0.0005	April	-0.6056	0.0493
Household Size/Composition			May	-0.5313	0.0474
1/HH_SIZE	-1.5844	0.0203	June	-0.5380	0.0482
PER_LT13	0.0591	0.0324	July	-0.6010	0.0477
PER_1317	0.5238	0.0368	August	-0.5388	0.0446
PER_GT65	-0.2916	0.0184	September	-0.5507	0.0481
Race/Ethnicity			October	-0.5202	0.0470
BLACK	-0.9699	0.0280	November	-0.3186	0.0399
ASIAN	-1.4703	0.1130			
SPANISH	-0.1332	0.0200	s_1^2	0.9504	0.0147
Regional Dummy Variables			s_2^2	3.4762	0.0125
ENC	-0.3554	0.0158	r	-0.0382	0.0048
ESC	-0.2279	0.0282	Estimated Correlation Coefficients		
MA	-0.3574	0.0154	d	0.1848	0.0019
MNT	-0.0908	0.0146	d_1	-0.0308	0.0036
NE	-0.2421	0.0174	d_2	0.2156	0.0031
SA	-0.2633	0.0152			
WNC	-0.5593	0.0210			
WSC	-0.2819	0.0155			

Note: All coefficients except that associated with the PER_LT13 variable are statistical significant at the 0.01 level. A pseudo R-square measure, calculated as the correlation between the dependent variable and the expected value, $E(Y_t)$, was 0.354.

Table 3: Comparison of Various Elasticities

	(1)	(2)	(3)	(4)	(5)	(6)
	$E(Y_t)$	$E(Y_t\|Y_{t-1}=0)$	$E(Y_t\|Y_t>0)$	$E(Y_t\|Y_t>0, Y_{t-1}=0)$	$Prob(Y_t>0)$	$Prob(Y_t>0\| Y_{t-1}=0)$
Estimated Value (Actual Value)	0.871 (0.849)	0.816 (0.650)	1.699 (1.732)	1.809 (1.666)	0.513 (0.490)	0.453 (0.390)
	Elasticity Estimates					
Long-Run ADV	0.0028*	0.0030	0.0010*	0.0010	0.0018*	0.0021*
NETPRICE	-0.8862*	-0.9734*	-0.3281*	-0.3388*	-0.5580*	-0.6794*
HHINC	0.0944*	0.1031*	0.0350*	0.0359*	0.0594*	0.0720*
HHSIZE	0.5200*	0.5680*	0.1927*	0.1977*	0.3277*	0.3965*
BASE_AGE	-0.0758*	-0.0822*	-0.0281*	-0.0286*	-0.0477*	-0.0574*
PER_LT13	0.0029	0.0031	0.0011	0.0011	0.0018	0.0021
PER_1317	0.0114*	0.0126*	0.0042*	0.0044*	0.0072*	0.0088*
PER_GT65	-0.0380*	-0.0420*	-0.0141*	-0.0146*	-0.0239*	-0.0293*

Note: * indicates significance at the 0.01 level.

Table 4. Baseline Parameter Values Used to Calculate Producer Net Producer Returns from Generic Cheese Advertising.

Item	Definition	Value
Q	1996-99 annual average cheese disappearance (Bil. Lbs. MFE; Kaiser, 2000)*	60.7
V	1996-99 annual average farm price, $/cwt. (Kaiser, 2000)	13.83
t	Producer assessment rate, $/cwt.	0.076**
A	Average annual generic cheese advertising expenditures ($ million)	46.01
x_{Q1}	Short-run supply elasticity (Kaiser, 2000)	0.09
x_{Q2}	Long-run supply elasticity (Kaiser, 2000)	0.20
x_A	Long-run generic cheese advertising elasticity	0.0028***
x_D	Absolute Value at-home own-price cheese purchase elasticity	0.8862***

Note: * MFE = Milk Fat Equivalent, **Calcualted as average annual generic cheese advertising expenditures divided by MFE cheese disappearance, ***Obtained from Table 3

Table 5. Marginal Net Returns to Producers Due to Generic Cheese Advertising and At-Home Cheese Consumption.*

Supply Elasticity	(1) Gross Return ($/Adv.$), $\frac{a}{x_Q + x_D}$	(2) Incidence of Levy ($), Γ	(1) - (2) Marginal Net Return ($), R
x_Q = 0.00	0.58	1.00	-0.42
x_Q = 0.09	0.52	0.91	-0.38
x_Q = 0.20	0.47	0.81	-0.34

Note: * Closed economy assumption ignoring trade effects.

Figure 1. Definition of Censored Strings with AR-1 Model

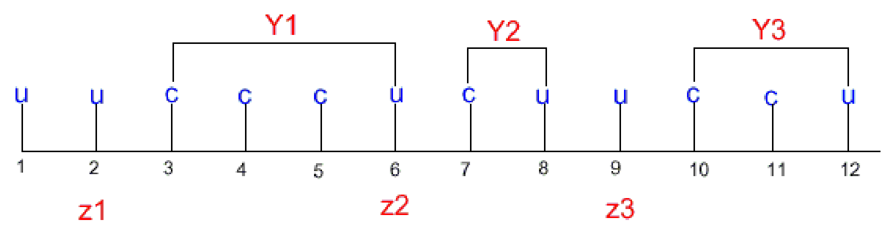


Figure 2. Illustrative Example of the Polynomial Distributed Lag Advertising Effect

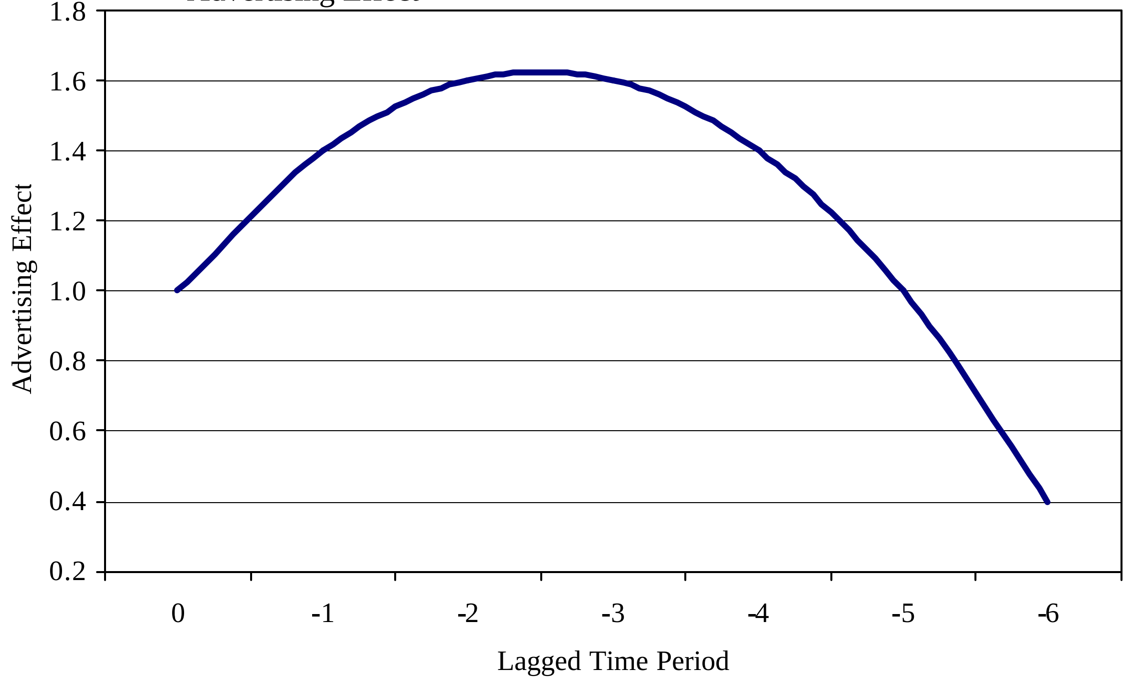


Figure 3. U.S. Generic Cheese Advertising Expenditures, Biweekly 1997-1999

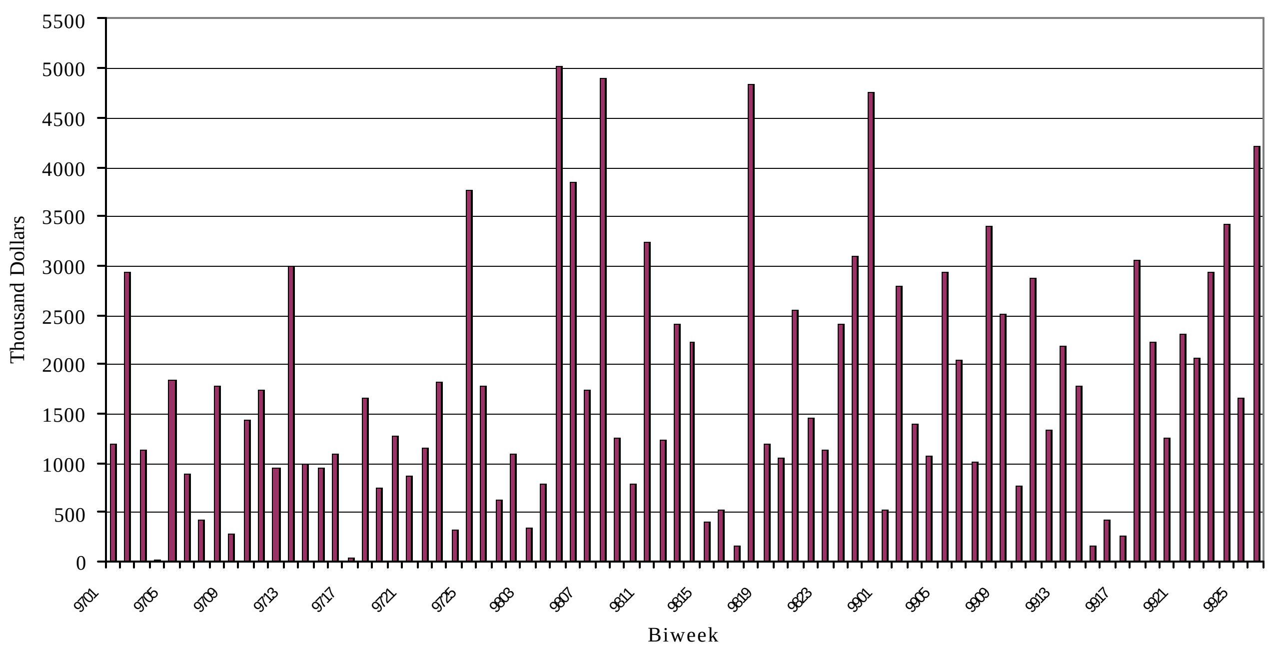
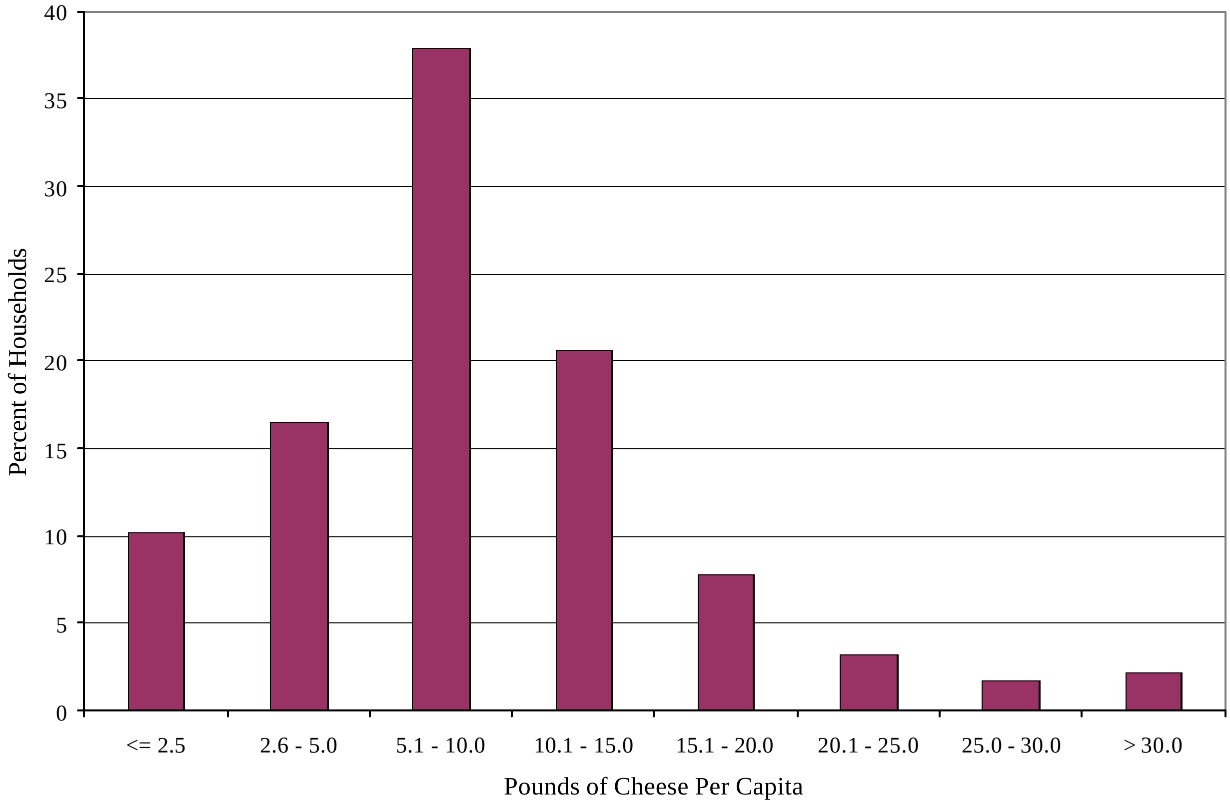


Figure 4. Household Annual Per Capita Cheese Purchase Distribution



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Footnotes

[1] For an example of an analysis that utilizes household level data for the analysis of generic promotion refer to Ward (1999).

[2] To account for stationarity, we assume $e_{i0} \sim \mathrm{N}\left(0, s_0^2\right)$ and $s_0^2 = \frac{s_1^2}{1-r}$.

[3] It should be noted that under this specification, the covariance does not vary across household. Although not accounted for here, to correct for possible heteroskedasticity, one may specify s_1^2 or s_2^2 or both as a function of household specific variables such as income and household size (Maddala).

[4] To simplify the notation, we ignore household subscripts. In general, a censored string ends after *p* consecutive uncensored observations. In our application, *p*=1.

[5] A dominant market area (DMA) is a group of counties in which stations located in the metro area achieve the largest audience share. DMA's are non-overlapping areas used for planning, buying and evaluating television audiences. Each county in the United States is assigned to only one DMA.

[6] As an alternative to the use of advertising expenditures, we could have used alternative measures of promotion effort such as gross rating points. We decided not to use such measures as they exclude exposure to print media.

[7] If desired, the individual lag advertising parameters can be recovered from the estimated value of l_2; i.e., $b_i = l_2(i^2 - \mathrm{L}i - (\mathrm{L}+1))$. Also, since $(i^2 - \mathrm{L}i - (\mathrm{L}+1)) < 0 \; \forall \; i$, the sign of β_i is the negative of the sign of λ_2 for all i .

[8] As Deaton (1987), Dong, Shonkwiler and Capps (1998) and Dong and Gould (2000) note, this method of calculating composite commodity price reflects not only differences in market prices faced by each household but also endogenously determined commodity quality. The zero-order price calculation was completed prior to the household random sampling to allow for a large number of households in each DMA.

[9] If there is not a female head present in the household, the male head characteristics are used.

[10] Alternative time periods were evaluated with very similar results and conclusions. For brevity, we limit our results here to one time period. Approximate standard errors are derived from the estimated parameter variance-covariance matrix: $\mathrm{Var}\left(\mathrm{d}(\Theta)\right) \approx C\Sigma_{\Theta}C'$ where $C = \frac{\partial \mathrm{d}(\Theta)}{\partial \Theta}$, Θ is the vector of estimated coefficients, $\mathrm{d}(\Theta)$ is the function defining the elasticities and Σ_{Θ} is the coefficient covariance matrix (Greene, 1997, pp.).

[11] A complete list of elasticity estimates is available from the authors upon request.

[12] While Kinnucan (1999) stresses the importance of considering trade effects when computing returns to advertising even when trade shares are modest, we have chosen to ignore this effect for our simple application of the at-home results. A more complex modeling strategy will be necessary to fully implement a benefit-cost analysis and the EDM application. We recognize that, ignoring trade effects will bias upwards the returns to advertising EDM calculation.