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Identifying the Effects of Generic Advertising on the Household Demand for Fluid Milk and Cheese: A Two-Step Panel Data Approach

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A two-step model with sample selection is applied to panel data of U.S. households to estimate at-home demand for fluid milk and cheese, incorporating advertising expenditures. The model consistently accounts for sample-selection bias, unobserved household heterogeneity, and temporal correlation. Generic advertising programs for fluid milk and cheese were effective at increasing conditional purchase quantities, with very little effect on the probability of purchase. In contrast to aggregate studies, the long-run generic advertising elasticities for cheese were larger than for those of fluid milk. Advertising response varied considerably across sub-product classes, while branded advertising expenditures were largely insignificant.

Key words: cheese, fluid milk, generic advertising, household demand, sample selection

Introduction

Since 1984, U.S. milk producers have contributed $0.15 per hundredweight of milk sold for activities designed to increase the demand for dairy products through generic advertising, promotion, and product research. In 1995, fluid milk processors joined the effort by enacting processor assessments of $0.20 per hundredweight on fluid milk sales to be used for advertising through the MilkPEP program. The combined checkoff programs annually collect more than $300 million (Kaiser).

Prior research on the impacts of generic dairy advertising is substantial. However, most studies focus on either national- or state-level response. Much less empirical work has been conducted on household-level, dairy product demand and determining the relative effectiveness of a generic advertising message across individual dairy products. A more micro-level approach can reveal information as to whether overall changes in demand are reflective of intensive responses (continuous adjustments), extensive responses

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(discrete changes), or both. The estimation approach used here extends previous two-step methods using cross-sectional data in two ways: first, we use a panel of U.S. households, and second, we account for unobserved household heterogeneity and serial correlation.

The objectives of this study are to (*a*) estimate household demands for both total and disaggregated fluid milk and cheese products, (*b*) decompose the demand effects into their discrete and continuous components, and (*c*) compare the relative effectiveness of generic advertising across individual products. We proceed with a brief description of the model, followed by a summary of the data used in the empirical application. Next, our econometric results are reported which identify differences between discrete and continuous demand impacts. We close with a few summary conclusions and directions for future research.

The Model

Given the nature of household purchases of disaggregated food categories, zero-purchase observations are expected, necessitating the use of econometric approaches accounting for censoring. One-step decision models, such as the tobit, imply simultaneity of the decisions to consume and consumption amounts. Haines, Guilkey, and Popkin argue that food consumption decisions should be modeled as a two-stage decision process where not only are the decisions separate, but also the determinants of each decision may differ. The general two-step process is typically represented by a first-stage dichotomous choice model (i.e., probit) of whether to purchase. Then a second-stage consumption model using only purchase observations is augmented with an additional variable (i.e., the inverse Mill's ratio) to control for selection bias (Heckman).

Such modeling procedures are common, and have been applied to general models of food consumption (e.g., Haines, Guilkey, and Popkin). Gould and Lin, and Heien and Wessells examined dairy product demand using this methodology. In a more recent investigation, Ward, Moon, and Medina apply the methodology to beef demand, incorporating generic beef promotion efforts as explanatory variables.

The estimation approach used here extends previous two-step methods using cross-sectional data via our use of a panel of U.S. households. Ignoring temporal and spatial linkages yields a pooled cross-sectional, two-step model that can be estimated using traditional maximum-likelihood (ML) procedures. However, if we relax this assumption and allow for unobserved household heterogeneity and state dependence, the second-stage process requires the use of all observations, both censored and uncensored, because there is an assumed relationship between current and prior period decisions.

Consider the demand for an individual product as follows:

$$(1)\qquad \begin{bmatrix} z_{ht}^* \\ y_{ht}^* \end{bmatrix} = \begin{bmatrix} \mathbf{W}_{ht}\gamma \\ \mathbf{X}_{ht}\beta \end{bmatrix} + \begin{bmatrix} v_{ht} \\ u_{ht} \end{bmatrix}, \quad \text{and} \quad \begin{cases} z_{ht} = 1 & \text{if } z_{ht}^* > 0, \quad \text{otherwise } z_{ht} = 0, \\ y_{ht} = y_{ht}^* & \text{if } z_{ht}^* > 0, \quad \text{otherwise } y_{ht} = 0, \end{cases}$$

$$h = 1, \ldots, H; \;\; t = 1, \ldots, T,$$

where z_{ht}^* and y_{ht}^* are the unobserved (latent) variables for household h at time t, corresponding to the observed dependent variables z_{ht} (the binary response variable) and y_{ht} (the censored continuous consumption variable), respectively; $\mathbf{W}_{ht}$ and $\mathbf{X}_{ht}$ are vectors of exogenous variables related to the response and consumption equations, respectively; H is the total number of households observed over a total of T periods; and γ and β are conformable parameter vectors. The two-step approach allows for the sets of explanatory variables to differ across equations; i.e., $\mathbf{W}_{ht}$ and $\mathbf{X}_{ht}$ may be different. In other words, some variables may be common to both equations, while other variables may be in one set, but not in the other.

To complete the model specification, the relationship of the error terms across equations, households, and time must be specified. Assuming the traditional probit specification for the first stage, we have:

$$z_{ht}^{*} = \mathbf{W}_{ht}\gamma + v_{ht}, \tag{2}$$

where

$$z_{ht} = \begin{cases} 1 & \text{if } z_{ht}^{*} > 0, \\ 0 & \text{otherwise,} \end{cases} \quad \text{and} \quad v_{ht} \sim N(0,1);\ h = 1, \ldots, H;\ t = 1, \ldots, T.$$

The log-likelihood function over H households can then be written as:

$$\ln \mathrm{L}_1 = \sum_{h=1}^{H} \left[\sum_{z_{ht}=1} \ln\big(\Phi(\mathbf{W}_{ht}\gamma)\big) + \sum_{z_{ht}=0} \ln\big(1 - \Phi(\mathbf{W}_{ht}\gamma)\big) \right], \tag{3}$$

where $\ln \mathrm{L}_1$ is the log-likelihood value of the first stage and $\Phi(\cdot)$ is the standard normal cumulative distribution function (CDF).

Equation (3) can be solved relatively easily by ML. However, when allowing for correlation among the binary responses, the algorithm becomes computationally intractable as T increases because one is required to define the joint distribution of $\mathbf{v}_h$ with a full variance-covariance matrix and solve over the T-fold integral. Although procedures for modeling dichotomous choice using time-series and panel data have been developed (e.g., Liang and Zeger; Butler and Moffitt; Dong and Gould), they have not been used in the context of a two-step sample selection model. To the authors' knowledge, the appropriate sample-correction procedure has not been developed for a two-step procedure under a nonconstant unit variance assumption for the probit model in which the serial correlation coefficient of the first stage affects this correction.[1]

Our approach extends the traditional two-step approach to panel data by providing consistent estimates of the dichotomous purchase decision and avoiding the evaluation of multi-dimensional integrals. Our procedure is similar to the two-step censored demand system approach of Shonkwiler and Yen, where the first stage is represented by single-equation probit models to provide consistent parameter estimates followed by a second-stage system estimation procedure accounting for across-equation correlation.

In our application, consistent estimates of γ are obtained and then applied in the second-stage demand response relation with an error structure accounting for unobserved household heterogeneity and state dependence. Ignoring potential correlation in the dichotomous model still yields consistent, although not necessarily efficient, estimates of the bias correction factor. The approach provides a computationally less

[1] The authors recognize the contributions of alternative formulations of the panel data, sample-selection problem which differ from the two-step approach (e.g., Kyriazidou; Wei; Charlier, Melenberg, and van Soest). Our goal here, however, is to develop an approach that retains the two-step structure for application to panel data.

burdensome way to address sample selection, while ensuring the panel nature of the data is exploited.

Given equations (1) and (2), the household error structure is defined as a multivariate normal (MN):

$$(4) \qquad \left[\mathbf{v}_h' \vdots \mathbf{u}_h'\right] \sim \mathrm{MN}\left[\mathbf{0}, \Sigma_h\right] \; \forall \; h = 1, \ldots, H,$$

where

$$\Sigma_h = \begin{bmatrix} \mathbf{I}_T & \delta\Omega_h^{½} \\ \delta\Omega_h^{½\prime} & \Omega_h \end{bmatrix},$$

and where $[\mathbf{v}_h' \vdots \mathbf{u}_h']$ is a $\{2T \times 1\}$ stacked vector, and $\mathbf{I}_T$ is a $\{T \times T\}$ identity matrix $\forall \; h = 1, \ldots, H$, and follows from the pooled cross-section specification of the standard probit model. The $\{T \times T\}$ covariance matrix Ω_h allows for unobserved household heterogeneity and state dependence. The error covariance is represented by $\mathrm{cov}(\mathbf{v}_h, \mathbf{u}_h) = \delta\Omega_h^{½} \; \forall \; h = 1, \ldots, H$, where $\Omega_h^{½}$ is the Cholesky decomposition of Ω_h, and the correlation of error equations is denoted by δ. Specifically, assume the error term u_{ht} consists of two components:

$$(5) \qquad u_{ht} = \alpha_h + \varepsilon_{ht}, \qquad h = 1, \ldots, H; \; t = 1, \ldots, T,$$

where α_h is uncorrelated with ε_{ht} being a household-specific, normal random variable used to capture household heterogeneity. State dependence is an empirical question, and a test for its existence can be quantified by adopting a particular autoregressive error structure. We assume ε_{ht} follows a first-order autoregressive process (AR1), i.e.:

$$(6) \qquad \varepsilon_{ht} = \rho\varepsilon_{ht-1} + e_{ht}, \qquad |\rho| < 1; \; h = 1, \ldots, H; \; t = 1, \ldots, T,$$

where ρ is the autocorrelation coefficient and $e_{ht} \sim N(0, \sigma_0^2) \; \forall \; h$ and t. Additionally, $\alpha_h \sim N(0, \sigma_2^2) \; \forall \; h$, and persists over time. To warrant stationarity, we assume $\varepsilon_{ht} \sim N(0, \sigma_1^2)$ and $\sigma_0^2 = \sigma_1^2(1 - \rho^2)$.

Combining equations (5) and (6) yields the household covariance matrix, Ω_h:

$$(7) \qquad \Omega_h = \sigma_2^2 \mathbf{J}_T + \sigma_1^2 \begin{bmatrix} 1 & \rho & \rho^2 & \cdots & \rho^{T-1} \\ \rho & 1 & \rho & \cdots & \rho^{T-2} \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ \rho^{T-2} & \rho^{T-3} & \cdots & \cdots & \rho \\ \rho^{T-1} & \rho^{T-2} & \cdots & \rho & 1 \end{bmatrix},$$

where $\mathbf{J}_T$ is a $\{T \times T\}$ matrix of ones, and Ω_h is invariant across households.[2]

Following Shonkwiler and Yen, we can express unconditional expected household purchases as:

$$(8) \qquad E(\mathbf{y}_h) = \left[\Phi(\mathbf{W}_h\gamma)\right] * \mathbf{X}_h\beta + \delta\Omega_h^{½}\phi(\mathbf{W}_h\gamma), \qquad \forall \; h = 1, \ldots, H,$$

[2] Although not accounted for here, to correct for possible heteroskedasticity, one may specify σ_1^2, σ_2^2, or both as a function of household variables such as income and household size.

where $\mathbf{y}_h$ is the $\{T \times 1\}$ vector of purchase quantities for household h; $\phi(\cdot)$ and $\Phi(\cdot)$ are $\{T \times 1\}$ standard normal probability density function (PDF) and CDF vectors evaluated at each $\{t = 1, \ldots, T\}$, respectively; and $\mathbf{W}_h$ and $\mathbf{X}_h$ are matrices of exogenous variables for each household $\{h = 1, \ldots, H\}$. The second component of (8) represents the sample-selection correction factor given the error structure defined in (4). The unconditional variance of $\mathbf{y}_h$ can then be expressed as:

(9)
$$\begin{aligned}\text{var}(\mathbf{y}_h) &= \text{var}\left(\mathbf{y}_h \mid \mathbf{z}_h^*\right) = \Omega_h - \delta\Omega_h^{1/2} * \mathbf{I}_T * \left(\delta\Omega_h^{1/2}\right)' \\ &= \Omega_h - \delta^2\Omega_h \equiv \Omega_h^*, \quad \forall h = 1, \ldots, H.\end{aligned}$$

The model parameters in (1) can be estimated by the following two-step procedure: (a) using all observations, obtain pooled cross-section ML estimates of γ, say $\hat{\gamma}$ via (1) and (2); and (b) use $\hat{\gamma}$ to compute the PDF and CDF terms in (8) and obtain ML estimates of β, δ, and Ω from:

(10)
$$\mathbf{y}_h = \left[\Phi(\mathbf{W}_h\hat{\gamma})\right]\mathbf{X}_h\beta + \delta\Omega_h^{1/2}\phi(\mathbf{W}_h\hat{\gamma}) + \hat{\mathbf{u}}_h.$$

The log likelihood of the second-stage regression ($\ln L_2$) may now be written as:

(11)
$$\ln L_2 = \sum_{h=1}^{H}\left[-\tfrac{1}{2}T * \ln(2\pi) - \tfrac{1}{2}\ln\left(\det(\Omega_h^*)\right) - \tfrac{1}{2}\hat{\mathbf{u}}_h'\,[\Omega_h^*]^{-1}\hat{\mathbf{u}}_h\right],$$

where $\hat{\mathbf{u}}_h$ is the household-specific $\{T \times 1\}$ residual vector derived from (10). Since the ML estimates $\hat{\gamma}$ are consistent, applying ML estimation to (10) produces consistent second-stage parameter estimates (Shonkwiler and Yen).

A problem caused by the use of the estimated $\hat{\gamma}$ in (9) is that the covariance matrix of the second-step estimator is incorrect. We correct for this by applying the Murphy and Topel procedure to derive the asymptotic covariance matrix of $\hat{\beta}$, say $\mathbf{V}_2^*$, as follows (Greene, p. 142):

(12)
$$\mathbf{V}_2^* = \mathbf{V}_2 + \mathbf{V}_2\left[\mathbf{C}\mathbf{V}_1\mathbf{C}' - \mathbf{R}\mathbf{V}_1\mathbf{C}' - \mathbf{C}\mathbf{V}_1\mathbf{R}'\right]\mathbf{V}_2,$$

where

$$\begin{aligned}\mathbf{V}_1 &= \text{var}[\hat{\gamma}] \text{ from } \ln L_1, \\ \mathbf{V}_2 &= \text{var}\left[\hat{\beta}\right] \text{ from } \ln L_2 \mid \hat{\gamma}, \\ \mathbf{C} &= E\left[\left(\frac{\partial \ln L_1}{\partial \beta}\right)\left(\frac{\partial \ln L_2}{\partial \gamma'}\right)\right], \text{ and} \\ \mathbf{R} &= E\left[\left(\frac{\partial \ln L_2}{\partial \beta}\right)\left(\frac{\partial \ln L_1}{\partial \gamma'}\right)\right].\end{aligned}$$

To evaluate the decomposition of intensive and extensive effects of household purchase behavior, we derive alternative elasticity measures. For time period t, expected purchase probabilities, conditional expected purchases, and unconditional expected purchases can be expressed respectively as:

(13)
$$\Pr\left[z_{ht} = 1\right] = \Phi(\mathbf{W}_{ht}\gamma),$$

(14) $$E(y_{ht} \mid y_{ht} > 0) = \mathbf{X}_{ht}\beta + \delta\sqrt{\sigma_1^2 + \sigma_2^2}\,\frac{\phi(\mathbf{W}_{ht}\gamma)}{\Phi(\mathbf{W}_{ht}\gamma)},$$

and

(15) $$E(y_{ht}) = \Phi(\mathbf{W}_{ht}\gamma) * \mathbf{X}_{ht}\beta + \delta\sqrt{\sigma_1^2 + \sigma_2^2}\,\phi(\mathbf{W}_{ht}\gamma).$$

The expected values of these equations, and ultimately the elasticities based on them, can be computed by substituting in the estimated coefficients of the model parameters. Because the unconditional expected purchase [equation (15)] is the product of the expected purchase probability [equation (13)] and the conditional expected purchase [equation (14)], it can be easily shown that the unconditional purchase elasticities are the sum of the conditional purchase and purchase probability elasticities. Approximate standard errors of the elasticities can be derived from the estimated parameter variance-covariance matrix using the delta method (Greene, p. 278).

Description of the Household Panel Data

Fluid milk and cheese purchase data for at-home consumption and annual household demographic data were obtained from the ACNielsen Homescan Panel sample of U.S. households from January 1996 through December 1999 (ACNielsen, Inc., © 2000). Households comprising the panel used hand-held scanners to record purchase information including date of purchase, Universal Product Code (UPC), total expenditure, and quantities purchased. In addition, households submit annual demographic information.

To provide consistency with the advertising data, our purchase data were aggregated to a monthly basis. Clarke recommends the use of monthly data in most situations to avoid "data interval bias" in the estimation of advertising effects. A random sample of 2,177 households, in the panel consistently over the four-year study period, was used in this analysis.

Table 1 provides an overview of household characteristic variables used in the analysis. Besides annual household pre-tax income (*INCOME*), the female head's education attainment (*COLLEGE*), employment status (*FH_WORKS*), and age (*FH_AGE*) are used as explanatory variables.[3] We also incorporate measures of household size (*HH_SIZE*), member age distribution, and two binary variables representing double income, no children households (*DINKS*) and young and single households (*YNGSNGL*). Dichotomous regional, race/ethnicity, and monthly variables are included to control for geographic, race-related, and seasonal variations in household purchase patterns, respectively.

Fluid milk was disaggregated into three subcategories: whole, low fat, and skim milk. Mean conditional purchase quantities, prices (net of coupon value redeemed), and purchase frequencies are shown in table 2. The mean conditional purchase for total milk was approximately 3.3 gallons per household, or 1.4 gallons per capita per month. Factoring in mean purchase frequency results in an estimated unconditional purchase quantity of approximately 1.2 gallons per capita per month. Low fat milk was the most popular fluid milk product, having the highest mean purchase frequency and proportion

[3] The *FH_WORKS* variable is equal to one if the female head works at least 30 hours per week outside of the home. The female head characteristic is also used for the classification of race/ethnicity variables. If there is not a female head present in the household, male head characteristics are used.

Table 1. Description of Household and Advertising Data Used in the Two-Step Model (1996–1999)

Variable	Description	Units	Mean [a]
Household Characteristics:			
INCOME	Annual household pre-tax income	$000s	48.54 (33.20)
COLLEGE	Female head completed college education	0/1	0.36
FH_WORKS	Female head works outside home	0/1	0.52
FH_AGE	Female head age	years	52.66 (13.18)
Household Size/Composition:			
HH_SIZE	Number of household members	no.	2.38 (1.26)
PR_LT13	Proportion of household members less than 13 years	no.	0.08 (0.16)
PR_1317	Proportion of household members age 13–17	no.	0.04 (0.11)
PR_GT65	Proportion of household members greater than 65 years	no.	0.23 (0.39)
DINKS	Two working adults, no children	0/1	0.14
YNGSNGL	Young (< 35) and single household	0/1	0.01
Household Race/Ethnicity:			
BLACK	Female head self-identifies as Black	0/1	0.07
ASIAN	Female head self-identifies as Asian	0/1	0.01
HISPANIC	Female head self-identifies as Hispanic (non-Black)	0/1	0.05
Household Geographic Location:			
METRO	Household resides in metropolitan location	0/1	0.85
NE_REG	North East region (CT, ME, MA, NH, RI, VT)	0/1	0.06
MA_REG	Mid-Atlantic region (DE, DC, MD, NJ, NY, PA, WV)	0/1	0.13
SA_REG	South Atlantic region (FL, GA, NC, SC, VA)	0/1	0.20
ESC_REG	East South Central region (AL, AR, KY, LA, MS, TN)	0/1	0.03
ENC_REG	East North Central region (IL, IN, MI, OH, WI)	0/1	0.14
WNC_REG	West North Central region (IA, MN, NE, ND, SD)	0/1	0.08
WSC_REG	West South Central region (KS, MO, OK, TX)	0/1	0.12
MNT_REG	Mountain region (AZ, CO, ID, MT, NV, NM, UT, WY)	0/1	0.11
Advertising Expenditures:			
USMLKADV	Monthly, national generic fluid milk advertising expenditures [b]	$mil.	12.19 (4.10)
BRMLKADV	Monthly, national brand fluid milk advertising expenditures [c]	$mil.	1.21 (0.70)
USCHZADV	Monthly, national generic cheese advertising expenditures [b]	$mil.	3.34 (1.63)
BRCHZADV	Monthly, national brand cheese advertising expenditures [c]	$mil.	6.22 (2.54)

Notes: Random sample = 2,177 households. Monthly dummy variables (M1–M11) are also included in the model to account for seasonality.

[a] Standard deviations are in parentheses for continuous variables.

[b] Data obtained from Dairy Management, Inc. (DMI).

[c] Data obtained from *Leading National Advertisers* (LNA).

Table 2. Mean Household Fluid Milk and Cheese Purchase Characteristics (1996–1999)

FLUID MILK					
Variable	Total	Whole	Low Fat	Skim	
Conditional Purchase (gal./mo.)[a]	3.29	2.24	2.86	2.61	
	(3.26)	(2.55)	(2.85)	(2.87)	
Conditional Net Price ($/gal.)[a]	2.84	3.06	2.73	2.84	
	(0.88)	(0.98)	(0.83)	(1.05)	
Coupon Use Frequency[a]	0.05	0.02	0.05	0.05	
Purchase Frequency	0.86	0.21	0.54	0.30	
Proportion of Households:[b]					
▸ Purchase at least once	0.99	0.68	0.91	0.68	
▸ Regular purchasers	0.91	0.18	0.54	0.29	
CHEESE					
Variable	Total	American	Mozzarella	Processed	Other
Conditional Purchase (lbs./mo.)[a]	2.47	1.29	1.17	1.69	1.24
	(2.25)	(1.16)	(1.05)	(1.49)	(1.17)
Conditional Net Price ($/lb.)[a]	3.29	3.39	3.52	2.94	3.70
	(1.30)	(0.99)	(1.10)	(1.19)	(1.90)
Coupon Use Frequency[a]	0.17	0.13	0.11	0.12	0.13
Purchase Frequency	0.72	0.31	0.18	0.38	0.43
Proportion of Households:[b]					
▸ Purchase at least once	0.99	0.91	0.81	0.96	0.97
▸ Regular purchasers	0.81	0.22	0.07	0.30	0.37

[a] Conditional purchase, net price (net of coupon value redeemed), and coupon use frequency are household averages (standard deviations) computed over purchase observations.
[b] Household proportions indicate the proportion of households that purchased each product at least once and on at least one-half of the months in the sample period (i.e., defined as regular).

of "regular" purchasing households.[4] The purchase statistics also give evidence of some multiple-product household purchases.

Cheese was disaggregated into American, mozzarella, processed, and other cheese categories. The "other" cheese category contains numerous varieties, including ricotta, Muenster, farmers, brick, and cream cheese. The mean conditional purchase amount was approximately 2.5 pounds per household, or 1.0 pound per capita per month. Unconditional purchases averaged nearly 0.8 pound per capita per month. Processed and other cheeses were the most commonly purchased varieties, followed closely by American cheese; however, households purchasing multiple varieties were common.

While these purchase amounts may seem low relative to U.S. Department of Agriculture (USDA) disappearance estimates (e.g., USDA annual cheese disappearance for 1997 was estimated at 28 pounds per capita), purchases in the data reflect purchases for at-home consumption only. The USDA estimate accounts for total cheese consumption—within and outside the home—as well as cheese contained in commercially manufactured and prepared foods. This non-home component has been estimated to account for

[4] A regular purchasing household was defined as a household that purchased the product on at least one-half of the sample period months.

as much as two-thirds of total cheese consumption (USDA). As such, the at-home purchase estimates here (approximately 10 pounds per capita annually) are in line with USDA projections.

Prices are not observed directly in the data. An estimate of price was obtained by dividing reported monthly expenditures (less any coupon value redeemed) by quantity purchased. A number of alternative approaches were considered to obtain estimates of unobserved prices during nonpurchase periods. For this analysis, we impute prices for nonpurchase observations for each household as being equal to the mean Dominant Market Area (DMA) net price for that monthly period.[5,6]

As expected, coupon use was infrequent for the fluid milk products, but considerably larger for the cheese products (table 2), and reflects use of either store or manufacturer coupons. The price effect of coupon redemption is reflected in the *Conditional Net Price* variable. However a binary variable representing coupon use is also included to account for changes in purchase amounts from coupon redemption in addition to the price effect. Prices are converted to real 2000 dollars using the national Consumer Price Index (CPI) for nonalcoholic beverages (milk) and fats and oils (cheese). Household income is deflated by the national CPI for all items.

Generic fluid milk and cheese advertising expenditure data were obtained from Dairy Management, Inc. (DMI), the firm that administers allocation of checkoff dollars. The advertising data are national in scope and aggregated across media type. As such, the advertising data varied across time, but not across households.[7] Monthly advertising expenditure data were not available at a regional or media-market level. Considering the advertising efforts are largely based on a national campaign, common expenditure data are hypothesized to adequately represent household advertising exposure. The national generic advertising expenditure data are also consistent with the available branded advertising expenditure data compiled from *Leading National Advertisers* (LNA), on a monthly, national basis.

Mean levels of advertising expenditure are included in table 1 for both generic and branded expenditures. Advertising expenditures were deflated by a composite media cost index (2000 = 1) provided by DMI. While mean expenditures on generic fluid milk advertising were higher than the corresponding branded expenditures, the opposite is true for cheese.

There is a large body of empirical evidence suggesting both current and lagged advertising efforts affect current purchase behavior (Forker and Ward; Ferrero et al.). To mitigate the impact of multicollinearity among the lagged advertising variables, the lag weights were approximated using a second-degree polynomial distributed lag (PDL) structure, with endpoints restricted to zero (e.g., see Liu et al.; Suzuki et al.; Kaiser). This structure requires the estimation of only one parameter and represents the quadratic

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[5] The DMA was created by Nielsen Media Research to measure television station ratings, and currently divides the United States into 210 market areas. Each county in the United States is assigned to only one DMA. Households were assigned a particular DMA code by their county of residence.

[6] The average price calculation was completed prior to the household random sampling to allow for a large number of households in each DMA. As noted by Cox and Wohlgenant, and by Dong, Shonkwiler, and Capps, this average price calculation reflects not only differences in market prices faced by each household, but also endogenously determined commodity quality.

[7] Prior research explaining micro-decisions with macro-data exists. Some examples with household data and generic advertising expenditures include Blisard et al.; Reynolds; and Ward, Moon, and Medina.

PDL parameter on the lag-weighted advertising variable. In general notation, the PDL structure with end-point restrictions can be written as:

(16)
$$\begin{aligned} y_t &= \alpha + \sum_{i=0}^{L} \beta_i ADV_{t-i} + e_t, \\ \text{s.t.: } \beta_i &= \lambda_0 + \lambda_1 i + \lambda_2 i^2, \\ \beta_{-1} &= \beta_{L+1} = 0, \end{aligned}$$

where L is the total lag length, β_i is the ith lag advertising coefficient, ADV_{t-i} is the total advertising expenditure level for period $t - i$, and all other variables are suppressed into α for notational convenience. After substituting, (16) simplifies to:

(17)
$$\begin{aligned} y_t &= \alpha + \lambda_2 ADV_t^* + e_t, \\ ADV_t^* &= \sum_{i=0}^{L} \big(i^2 - Li - (L + 1)\big) ADV_{t-i}. \end{aligned}$$

Expenditures on generic and brand advertising are included as explanatory variables in both stages of the milk and cheese models with a six-month PDL structure. Alternative lag lengths were evaluated based on previous studies of generic advertising for dairy products (e.g., Kaiser; Lenz, Kaiser, and Chung). The six-month lag length selected is within the boundaries established by Clarke, who concluded that 90% of the cumulative effects of advertising for frequently purchased products is captured within three to nine months. The estimated coefficient on the advertising lag-weighted variable represents the quadratic PDL parameter as illustrated above, from which long-run advertising effects can be computed.[8]

Estimation Results

Following the model structure outlined above, two-stage models of sample selection were estimated for aggregated fluid milk and cheese, as well as for the individual sub-product classes. Parameter estimates were obtained by maximizing the likelihood functions in (3) and (11) using GAUSS software. Net price and income variables were included as natural logarithm transformations of the original data to reflect the a priori hypothesis of diminishing marginal effects associated with these demand factors. For similar reasoning, but to avoid the possible problem of zero-level expenditures, advertising expenditures were transformed by their square root.

The estimated coefficients are included in appendix tables A1–A4. For brevity, we refer the reader to these tables for evaluation of specific estimated parameters. We briefly highlight some of these results with respect to the sample-selection and variance effects. Because the conditional and unconditional demand effects are functions of the estimated parameters from both stages of estimation in a nonlinear fashion, it is best to evaluate the effects using computed elasticities.

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[8] The individual lag advertising parameters can be recovered from the estimated value of λ_2; i.e., $\beta_i = \lambda_2(i^2 - Li - (L + 1))$. Since $(i^2 - Li - (L + 1)) < 0 \ \forall\, i$, the $\text{sign}(\beta_i) = -\text{sign}(\lambda_2) \ \forall\, i$.

Significance of sample-selection bias is based on the significance of the estimated δ parameter on the PDF variable, ϕ. Sample-selection bias was not statistically important in either the aggregate fluid milk or cheese categories (appendix tables A2 and A4), but was significant for whole milk and the mozzarella, processed, and other categories for cheese.

The estimated variance parameters associated with serial dependence (σ_1 and ρ) and household heterogeneity (σ_2) were significant in all equations. From these coefficients, the correlation between current and previous month's purchases can be calculated as $\varphi = (\sigma_1^2\rho + \sigma_2^2)/(\sigma_1^2 + \sigma_2^2)$. The estimated values for total milk and cheese were $\varphi_{milk} = 0.75$ and $\varphi_{cheese} = 0.33$, implying current purchases are positively related to lagged purchases. Individual product classes had similar results, ranging from 0.79 to 0.84 for fluid milk products, and 0.23 to 0.35 for cheese products.[9]

The overall effect can be decomposed into serial state dependence ($\varphi^{SSD} = \sigma_1^2\rho/(\sigma_1^2 + \sigma_2^2)$) and household heterogeneity ($\varphi^{HH} = \sigma_2^2/(\sigma_1^2 + \sigma_2^2)$) components. The decomposition allows for segmenting the amount of correlation in the panel data into its time-series (e.g., habit persistence) and cross-sectional (e.g., household variability) components. From this decomposition, we find both sub-effects are positive. Household heterogeneity effects ($\varphi_{milk}^{HH} = 0.66$ and $\varphi_{cheese}^{HH} = 0.29$) contributed approximately 88% of the total correlation, and serial state dependence ($\varphi_{milk}^{SSD} = 0.09$ and $\varphi_{cheese}^{HH} = 0.04$) about 12%. Sub-product classes demonstrated similar proportional effects.

The positive correlation effects of household heterogeneity and serial dependence have important implications when evaluating long-term shifts in purchases from advertising. If advertising results in a positive shift in household purchases, which is then persistent over time, the positive effect of this strategy (φ^{HH}) is reinforced by the positive serial correlation effect (φ^{SSD}).

The elasticities for selected variables are included in table 3 for fluid milk and table 4 for cheese. The purchase probability elasticity (the extensive effect) represents the percentage change in purchase probability for a 1% change in the selected variable.[10] The conditional purchase elasticity (the intensive effect) represents the percentage change in the quantity demanded, given a purchase, for a 1% change in the selected variable.

For both the total fluid milk and cheese categories, all unconditional elasticities are dominated by intensive, conditional purchase effects, rather than purchase probability effects. This result could be due to the level of temporal aggregation (i.e., monthly) and the products' limited shelflife. The level of intensive effects is reduced for the sub-product categories and is dominated by purchase probability effects for some explanatory variables and products. In particular, purchase probability effects for household income are generally much more elastic than the conditional purchase effects for the sub-product categories.

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[9] Approximate standard errors of the correlation coefficients were computed using the delta method (Greene, p. 278) and are available from the authors upon request. Given the strong significance of the residual variance and autocorrelation terms, it is not surprising that all correlation coefficients computed were also highly significant (i.e., all were above a 99% confidence level).

[10] Given the panel nature of the data, increases in purchase probability could be attributed either to new households purchasing the product that didn't purchase previously or to existing purchasing households purchasing the product more frequently. As such, the terms "purchase probability" or "purchase frequency" are equally applicable.

Table 3. Fluid Milk Products: Elasticities of Household Demand at Sample Means

Variable	Total Milk	Whole	Low Fat	Skim
Purchase Probability Elasticities (A):				
Net Price	-0.066*	-0.896*	-0.398*	-0.735*
	(0.002)	(0.007)	(0.004)	(0.005)
Household Income	0.011*	-0.241*	-0.008*	0.295*
	(0.001)	(0.003)	(0.001)	(0.002)
Household Size	0.096*	0.378*	0.205*	-0.051*
	(0.001)	(0.005)	(0.002)	(0.003)
Age of Female Head	0.010*	-0.097*	0.014*	0.111*
	(0.002)	(0.011)	(0.005)	(0.007)
Proportion of Members Age < 13	0.003*	0.003*	0.011*	0.011*
	(0.001)	(0.001)	(0.000)	(0.001)
Proportion of Members Age 13–17	0.002*	-0.025*	0.012*	-0.009*
	(0.000)	(0.002)	(0.000)	(0.001)
Proportion of Members Age > 65	0.005*	-0.054*	0.027*	0.013*
	(0.000)	(0.002)	(0.001)	(0.001)
Long-Run Generic Milk Advertising	0.037*	-0.137*	-0.018	0.018
	(0.009)	(0.047)	(0.022)	(0.039)
Long-Run Brand Milk Advertising	0.006	0.017	-0.004*	-0.010
	(0.004)	(0.018)	(0.009)	(0.017)
Conditional Purchase Elasticities (B):				
Net Price	-0.177*	-1.420*	-0.227*	-0.754*
	(0.009)	(0.176)	(0.015)	(0.105)
Household Income	0.023*	-0.160*	0.020	0.118*
	(0.008)	(0.048)	(0.013)	(0.033)
Household Size	0.225*	0.334*	0.277*	0.212*
	(0.018)	(0.085)	(0.028)	(0.061)
Age of Female Head	-0.405*	-0.665*	-0.545*	-0.637*
	(0.048)	(0.255)	(0.088)	(0.205)
Proportion of Members Age < 13	0.031*	0.093*	0.016*	0.036*
	(0.003)	(0.020)	(0.004)	(0.012)
Proportion of Members Age 13–17	0.014*	0.025*	0.015*	0.011
	(0.002)	(0.009)	(0.002)	(0.006)
Proportion of Members Age > 65	0.010	-0.019	0.022*	0.032
	(0.006)	(0.027)	(0.009)	(0.020)
Long-Run Generic Milk Advertising	0.114*	-0.142	0.210*	0.106
	(0.020)	(0.090)	(0.031)	(0.061)
Long-Run Brand Milk Advertising	-0.011	0.077	-0.013	-0.017
	(0.009)	(0.042)	(0.014)	(0.031)
Unconditional Purchase Elasticities (A + B):				
Net Price	-0.243*	-2.317*	-0.624*	-1.489*
	(0.009)	(0.176)	(0.015)	(0.105)
Household Income	0.034*	-0.401*	0.011	0.412*
	(0.008)	(0.049)	(0.013)	(0.034)
Household Size	0.321*	0.711*	0.482*	0.161*
	(0.017)	(0.086)	(0.028)	(0.060)
Age of Female Head	-0.395*	-0.762*	-0.530*	-0.526*
	(0.048)	(0.255)	(0.089)	(0.205)
Proportion of Members Age < 13	0.034*	0.096*	0.027*	0.046*
	(0.003)	(0.020)	(0.004)	(0.012)
Proportion of Members Age 13–17	0.015*	0.000	0.027*	0.001
	(0.002)	(0.008)	(0.002)	(0.007)
Proportion of Members Age > 65	0.016*	-0.073*	0.049*	0.045*
	(0.006)	(0.027)	(0.010)	(0.021)
Long-Run Generic Milk Advertising	0.150*	-0.279*	0.192*	0.124*
	(0.020)	(0.094)	(0.031)	(0.061)
Long-Run Brand Milk Advertising	-0.005	0.094*	-0.017	-0.027
	(0.009)	(0.044)	(0.014)	(0.031)

Notes: Numbers in parentheses are standard errors. An asterisk (*) denotes significance at the 5% level. Significance is based on standard errors calculated using the delta method (Greene, p. 278).

Table 4. Cheese Products: Elasticities of Household Demand at Sample Means

Variable	Total Cheese	American	Mozzarella	Processed	Other
Purchase Probability Elasticities (A):					
Net Price	-0.167*	-0.804*	-0.648*	-0.585*	-0.532*
	(0.003)	(0.008)	(0.012)	(0.005)	(0.004)
Household Income	0.032*	0.039*	0.086*	-0.027*	0.135*
	(0.001)	(0.003)	(0.005)	(0.003)	(0.002)
Household Size	0.171*	0.371*	0.497*	0.379*	0.221*
	(0.002)	(0.005)	(0.010)	(0.004)	(0.004)
Age of Female Head	-0.059*	-0.177*	-0.847*	-0.080*	-0.008
	(0.005)	(0.011)	(0.021)	(0.010)	(0.010)
Proportion of Members Age < 13	0.013*	0.017*	0.040*	0.017*	0.020*
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Proportion of Members Age 13–17	0.006*	0.009*	0.019*	0.014*	0.010*
	(0.000)	(0.001)	(0.002)	(0.001)	(0.001)
Proportion of Members Age > 65	0.000	0.005*	-0.008*	-0.011*	0.002
	(0.001)	(0.002)	(0.004)	(0.001)	(0.001)
Long-Run Generic Cheese Advertising	-0.016	0.180*	-0.112*	-0.123*	-0.019
	(0.016)	(0.041)	(0.056)	(0.034)	(0.033)
Long-Run Brand Cheese Advertising	-0.008	0.014	-0.036	-0.072*	-0.029
	(0.011)	(0.028)	(0.038)	(0.023)	(0.022)
Conditional Purchase Elasticities (B):					
Net Price	-0.488*	-0.875*	-2.619*	-1.194*	-1.191*
	(0.012)	(0.040)	(0.166)	(0.047)	(0.048)
Household Income	0.039*	0.026	0.040	-0.006	0.115*
	(0.012)	(0.027)	(0.036)	(0.022)	(0.022)
Household Size	0.292*	0.339*	0.249*	0.301*	0.249*
	(0.019)	(0.045)	(0.063)	(0.037)	(0.037)
Age of Female Head	-0.336*	-0.278*	-0.945*	-0.369*	-0.107
	(0.048)	(0.120)	(0.166)	(0.095)	(0.077)
Proportion of Members Age < 13	0.016*	0.010	0.079*	0.016*	0.020*
	(0.003)	(0.007)	(0.012)	(0.007)	(0.006)
Proportion of Members Age 13–17	0.012*	0.007	0.031*	0.014*	0.015*
	(0.002)	(0.005)	(0.005)	(0.003)	(0.004)
Proportion of Members Age > 65	-0.014	-0.024	-0.009	-0.015	-0.011
	(0.007)	(0.013)	(0.027)	(0.014)	(0.012)
Long-Run Generic Cheese Advertising	0.256*	-0.046	0.238	0.147	0.965*
	(0.043)	(0.083)	(0.169)	(0.081)	(0.087)
Long-Run Brand Cheese Advertising	0.042	0.114*	0.010	0.009	0.159*
	(0.024)	(0.043)	(0.093)	(0.043)	(0.045)
Unconditional Purchase Elasticities (A + B):					
Net Price	-0.654*	-1.678*	-3.267*	-1.779*	-1.723*
	(0.012)	(0.040)	(0.166)	(0.047)	(0.048)
Household Income	0.071*	0.065*	0.126*	-0.033	0.249*
	(0.012)	(0.027)	(0.036)	(0.022)	(0.022)
Household Size	0.463*	0.710*	0.745*	0.680*	0.470*
	(0.020)	(0.045)	(0.064)	(0.037)	(0.037)
Age of Female Head	-0.395*	-0.456*	-1.792*	-0.449*	-0.116
	(0.048)	(0.120)	(0.166)	(0.095)	(0.078)
Proportion of Members Age < 13	0.030*	0.027*	0.119*	0.033*	0.041*
	(0.003)	(0.007)	(0.012)	(0.008)	(0.006)
Proportion of Members Age 13–17	0.019*	0.017*	0.050*	0.028*	0.025*
	(0.002)	(0.005)	(0.006)	(0.004)	(0.004)
Proportion of Members Age > 65	-0.014	-0.019	-0.017	-0.026	-0.009
	(0.008)	(0.013)	(0.026)	(0.015)	(0.012)
Long-Run Generic Cheese Advertising	0.240*	0.135	0.126	0.023	0.946*
	(0.042)	(0.083)	(0.168)	(0.079)	(0.087)
Long-Run Brand Cheese Advertising	0.033	0.128*	-0.026	-0.062	0.130*
	(0.023)	(0.044)	(0.095)	(0.043)	(0.045)

Notes: Numbers in parentheses are standard errors. An asterisk (*) denotes significance at the 5% level. Significance is based on standard errors calculated using the delta method (Greene, p. 278).

Price elasticities are significant for all products and types of elasticity. Unconditional price responses are inelastic for both fluid milk (-0.24) and cheese (-0.65), but the cheese price response is nearly three times as large. Since the price offered for one product (for a particular household) is not available when an alternative product is purchased, we do not include alternative product prices in the demand specifications. Consequently, sub-product elasticities are considerably higher than their respective aggregate-product levels, likely due to product switching and households purchasing multiple products. For example, a decrease in the skim milk price may induce, say, regular low fat drinking households to temporarily switch purchases to skim milk to take advantage of the price reduction. This change in price would affect both sub-product purchases, but would have no impact on the aggregate price effect, unless changes in purchased amounts also resulted from the price reduction.

The sub-product price elasticities for fluid milk are larger than elasticities reported by Gould, but more similar in magnitude to those found by Boehm and by Reynolds. The cheese price elasticities are similar to findings of Gould and Lin who estimated a total cheese price elasticity of -0.57 and elastic price responses for nearly all sub-classes evaluated. An elastic price response for natural cheese was also obtained by Blisard and Blaylock using household cheese purchase data.

Household income elasticities are positive and slightly larger for cheese than fluid milk. However, the sub-product categories demonstrate both positive and negative income elasticities. While negative income effects for whole milk are not uncommon (e.g., Cornick, Cox, and Gould; Boehm; Reynolds), the estimated income effect for low fat milk is not statistically significant. Income elasticities are consistent with those estimated by Cornick, Cox, and Gould, as well as Reynolds, where both studies report higher income elasticities for whole and skim milk products. For cheese, only the processed cheese category has a negative income effect. The income elasticities are similar to the aggregate cheese estimate of 0.045 in Gould and Lin, and in Gould, Cornick, and Cox for full fat natural American (0.06) and processed (-0.05) cheeses.

As expected, household size is positively related to both purchase probability and purchase levels for fluid milk and cheese. The household size elasticities for fluid milk are similar in magnitude to the elasticities found by Cornick, Cox, and Gould, and also declined in magnitude as the fat content lowered. The age of the female household head is negatively related to purchase probability and purchase levels for nearly all products evaluated, especially for cheese products.

Our findings reveal household composition is important, particularly highlighting higher purchase probabilities for households with children (both teenagers and children under the age of 13), relative to mature adult households. A higher proportion of senior citizens in the households also contributed positively to household milk purchases, but was not significant for cheese. With the exception of whole milk, household composition effects on sub-products are of similar sign. The lower teenager elasticities relative to young children seem consistent with higher dietary calcium needs of young children and the concern of milk marketers that teenagers are turning toward other nonalcoholic beverages as their diets become less closely monitored. Household composition elasticities for cheese products demonstrate similar effects. Gould, Cornick, and Cox also estimated positive age composition effects for household members under age 17 for cheese products except for reduced-fat American cheese; however, they did show positive contributions for households with members above age 65.

Advertising expenditure elasticities are especially interesting. Branded advertising efforts are not significant for either the total fluid milk or total cheese categories, and only a few sub-product categories show significant results—American and other cheese, and whole milk. This result is intuitively appealing given brand advertising's focus on increasing purchases at the expense of competitors, suggesting little, if any, effect at the nonbrand-specific product level. While a substantial amount of cheese advertising is brand specific, neither Sun, Blisard, and Blaylock, nor Blisard et al. found significant brand effects for natural cheese, and both studies combined the generic and brand advertising expenditures in the processed cheese model due to the preponderance of one dominant advertiser in the brand market.

For both total fluid milk and cheese, the unconditional long-run elasticities for generic advertising are positive, significant, and largely the result of intensive responses, i.e., from the conditional purchase effects. Specifically, only 25% of the total long-run generic advertising response for total fluid milk is the result of an increase in the probability of purchase, and the purchase probability effect is not significantly different from zero for total cheese.

The total milk and cheese generic advertising elasticities (0.15 for fluid milk, and 0.24 for cheese) are higher than those estimated by Kaiser (0.05 for fluid milk and 0.02 for cheese) using aggregate quarterly disappearance data from 1975–1999. Differences in the level of estimated elasticities could be due, in part, to differences in the level of temporal aggregation; however, the relative size of the elasticities between fluid milk and cheese is clearly different. Kaiser's aggregate estimates also use a more distant history of disappearance data and account for both at-home and away-from-home purchases. The latter is particularly important for cheese, where as much as two-thirds of total disappearance is consumed away from home or contained in manufactured food products. Because generic advertising focuses predominantly on at-home consumption, it is appealing to supporters of generic advertising that the estimated results here are above those estimated in more aggregated studies.

Interpretation of the sub-product generic advertising elasticities is less clear. In particular, while all unconditional long-run advertising elasticities are significant for the fluid milk products, the whole milk category is negative in sign. Few sub-product advertising elasticities are significant for the cheese products. One exception is the other cheese category, where the conditional and unconditional purchases are relatively large and significant. American cheese purchases do demonstrate a positive and significant purchase probability effect, giving some evidence of increasing household purchase frequency; however, mozzarella and processed cheese purchase probability effects are negative and significant. The generic advertising message is largely nonproduct specific, and the results shown here may be due to product switching and/or multiple product purchases over time. The negative result for whole milk may be explained by a cohort effect or households moving purchases to lower fat products. In any event, the generic advertising results have significant long-run impacts on low fat and skim milk products, as well as on the other cheese category.

In the literature on household milk demand, it is rare to find advertising as an explanatory variable. One exception is Reynolds, who used current national Canadian advertising expenditures and aggregated household price and quantity data to estimate considerably higher elasticities for total and whole milk (0.37 and 1.04, respectively). However, no significant response was found for low fat or skim milk.

The generic cheese advertising results here are in contrast to those obtained by Blisard et al. Using cross-sectional data, Blisard et al. found generic advertising was successful in inducing people into the natural cheese market, but this advertising did not influence current consumers. However, for processed cheese, they concluded both effects contributed positively to household demand. The results here demonstrate that generic cheese advertising has recently had no effect on increasing the probability of purchase or frequency of purchases, but has had a significant impact on increasing overall purchase quantities through increased conditional purchases.

The overall impact of the generic advertising programs on total milk or cheese purchases is what is of most importance to milk marketers and producers. Positive and significant purchase effects from generic advertising suggest these efforts have been effective at enhancing demand at the household level. Furthermore, focusing specifically on the at-home consumption component also confirms that cheese advertising efforts are relatively more effective than efforts directed at fluid milk advertising—a comparison not available in more aggregate studies.

Conclusions

U.S. milk producers and processors contribute substantial dollars each year to fund national generic advertising programs for fluid milk and cheese. Producers, marketers, and legislators are all interested in whether generic advertising increases consumer demand for dairy products. The household approach followed here allows for examination of the relative effectiveness of these programs on increasing at-home consumption of fluid milk and cheese products. In addition, a unique two-stage panel data estimation procedure permits decomposition of the total advertising effects into their extensive (probability of purchase) and intensive (purchase quantity level) components, and accounts for unobserved household heterogeneity and temporal correlation.

In general, the demand effects for aggregate fluid milk and cheese products were predominantly intensive—i.e., they affect the conditional purchase levels. However, the sub-product results reveal that household income and household size exhibited larger purchase probability or frequency effects. These higher extensive contributions were muted in the aggregate categorization, a possible result of product switching.

Brand advertising was largely ineffective at increasing household purchases of fluid milk and cheese at the aggregate or sub-product levels. Given brand advertising's objective of gaining market share from competing products, this is an intuitively appealing result. Generic advertising, however, displayed positive and significant effects on both aggregate fluid milk and cheese. Generic advertising appears more effective at increasing at-home purchases of cheese than purchases of fluid milk. These results are in contrast to more aggregate studies of generic advertising where national disappearance data are used. The household approach used here directs the focus to at-home consumption effects only and is consistent with marketers' target audience and use of generic, nonproduct-specific advertising messages.

Given the higher response to generic advertising for cheese compared to the relatively low estimates from aggregate studies using total cheese disappearance, it may be worthwhile investigating the expansion of the cheese advertising program to purchases away from home. The incidence of response to the advertising programs on purchases for at-home consumption was clearly from the intensive, purchase quantity effect. Fluid milk advertising had a small effect on increasing household purchase probabilities, while cheese advertising showed no significant effect. Response across sub-product classes varied considerably, highlighting the differences in response to specific products from generic advertising messages.

Given the complexities associated with modeling household food purchase behavior, these estimates provide a preliminary assessment of household demand for dairy products. Future research should analyze advertising response by specific product groups within fluid milk and cheese categories. Yet, modeling this response is more difficult. Because price, advertising, and other effects may induce product switching, a multinomial framework may be appropriate. However, the fact that the price of one product is not available when an alternative product is purchased leads to some difficult data and modeling problems.

Specific advertising information by geographic area is needed to more accurately measure household response to the advertising message received. If advertising expenditures are used, then accounting for differences in advertising costs (e.g., air time costs per minute) is needed across market areas. In this way, advertising expenditure dollars are reflective of actual advertising exposure across market areas. Finally, incorporating differences in product quality would help to isolate the quality component now included in the total price effect.

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Table A1. Maximum-Likelihood First-Stage Probit Parameter Estimates, by Milk Product Type

	Total Milk		Whole		Low Fat		Skim	
Variable	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Intercept	1.270*	0.090	1.139*	0.084	1.103*	0.076	-1.073*	0.085
ln(*NET_PRICE*)	-0.280*	0.009	-0.640*	0.005	-0.538*	0.005	-0.630*	0.004
ln(*INCOME*)	0.046*	0.002	-0.172*	0.002	-0.011*	0.002	0.253*	0.002
HH_SIZE^{-1}	-0.740*	0.007	-0.492*	0.006	-0.507*	0.005	0.080*	0.005
FH_AGE	0.001*	0.000	-0.001*	0.000	0.000*	0.000	0.002*	0.000
PR_LT13	0.195*	0.013	0.029*	0.009	0.200*	0.008	0.120*	0.008
PR_1317	0.169*	0.019	-0.449*	0.011	0.409*	0.010	-0.199*	0.010
PR_GT65	0.099*	0.006	-0.167*	0.004	0.159*	0.004	0.048*	0.004
USMLKADV PDL[a]	-0.034*	0.008	0.021*	0.007	0.005	0.007	-0.003	0.007
BRMLKADV PDL[a]	-0.034	0.021	-0.016	0.018	0.007	0.017	0.011	0.020
COLLEGE	-0.021*	0.003	-0.079*	0.002	-0.011*	0.002	0.143*	0.002
FH_WORKS	-0.134*	0.004	-0.034*	0.003	-0.075*	0.003	-0.130*	0.003
YNGSNGL	0.359*	0.016	-0.181*	0.011	0.494*	0.010	-0.202*	0.010
DINKS	-0.004	0.005	-0.120*	0.004	0.000	0.004	0.066*	0.003
BLACK	-0.412*	0.005	0.345*	0.004	-0.381*	0.004	-0.390*	0.004
ASIAN	-0.354*	0.010	0.420*	0.008	-0.508*	0.008	-0.146*	0.008
HISPANIC	-0.165*	0.007	0.307*	0.005	-0.195*	0.005	-0.129*	0.005
METRO	-0.017*	0.004	-0.040*	0.003	-0.044*	0.003	0.183*	0.003
NE_REG	-0.003	0.006	0.269*	0.005	-0.149*	0.004	-0.195*	0.004
MA_REG	0.098*	0.005	0.009*	0.004	-0.062*	0.003	0.026*	0.003
SA_REG	0.021*	0.004	0.314*	0.004	-0.215*	0.003	-0.032*	0.003
ESC_REG	-0.012	0.009	0.370*	0.006	-0.457*	0.006	-0.006	0.006
ENC_REG	0.114*	0.006	-0.318*	0.004	0.037*	0.003	-0.054*	0.004
WNC_REG	0.149*	0.007	-0.574*	0.006	0.020*	0.004	0.190*	0.004
WSC_REG	0.029*	0.005	-0.059*	0.004	-0.103*	0.004	-0.066*	0.004
MNT_REG	-0.136*	0.005	-0.012*	0.004	-0.040*	0.004	-0.163*	0.004
JANUARY	0.203*	0.040	0.061	0.042	0.104*	0.038	0.111*	0.046
FEBRUARY	0.040	0.036	-0.017	0.041	0.013	0.037	0.051	0.046
MARCH	0.089*	0.037	0.038	0.039	0.042	0.037	0.056	0.044
APRIL	-0.019	0.035	-0.055	0.040	-0.029	0.036	0.003	0.043
MAY	0.000	0.036	-0.070	0.040	-0.015	0.037	-0.007	0.045
JUNE	-0.022	0.035	-0.082*	0.039	-0.022	0.036	-0.004	0.044
JULY	0.066*	0.032	-0.032	0.036	0.004	0.033	0.017	0.038
AUGUST	0.171*	0.034	0.008	0.036	0.061	0.033	0.056	0.040
SEPTEMBER	0.025	0.032	-0.059	0.036	-0.020	0.033	0.004	0.040
OCTOBER	-0.003	0.033	-0.065	0.037	-0.016	0.033	0.009	0.040
NOVEMBER	0.034	0.033	-0.006	0.037	0.017	0.035	0.012	0.042
Log Likelihood	-34,647		-44,620		-60,720		-53,938	

Note: An asterisk (*) denotes significance at the 5% level.
[a] Advertising expenditures are included as a quadratic polynomial distributed lag (PDL) with endpoints restricted to zero. The coefficient represents the estimated lag-weighted PDL parameter estimate, λ_2 (see text for a detailed description).

Table A2. Maximum-Likelihood Second-Stage Parameter Estimates, by Milk Product Type

	Total Milk		Whole		Low Fat		Skim	
Variable	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error	Estimate	Std. Error
Intercept	4.963*	0.318	18.139*	1.557	5.240*	0.415	2.172*	0.659
ln(*NET_PRICE*)	-0.617*	0.018	-5.525*	0.130	-0.674*	0.017	-1.562*	0.029
ln(*INCOME*)	0.081*	0.028	-0.619*	0.146	0.058	0.040	0.243	0.058
HH_SIZE^{-1}	-1.431*	0.094	-2.364*	0.442	-1.503*	0.116	-0.800*	0.197
FH_AGE	-0.027*	0.003	-0.049*	0.015	-0.031*	0.005	-0.025*	0.007
PR_LT13	1.425*	0.118	4.836*	0.556	0.636*	0.164	0.987*	0.302
PR_1317	1.190*	0.128	2.447*	0.781	1.112*	0.165	0.549	0.308
PR_GT65	0.152	0.092	-0.318	0.464	0.276*	0.109	0.286	0.173
USMLKADV PDL [a]	-0.087*	0.014	0.121	0.077	-0.137*	0.018	-0.048	0.028
BRMLKADV PDL [a]	0.052	0.043	-0.410	0.215	0.053	0.055	0.049	0.089
COLLEGE	0.027	0.050	-0.549*	0.192	-0.135*	0.061	0.289*	0.123
FH_WORKS	-0.398*	0.029	-0.793*	0.156	-0.302*	0.035	-0.365*	0.067
YNGSNGL	0.006	0.243	-0.388	1.635	0.079	0.295	0.207	0.751
DINKS	0.079	0.042	-0.277	0.174	0.033	0.057	0.195*	0.098
BLACK	-1.215*	0.178	-0.274	0.489	-1.248*	0.246	-1.406*	0.406
ASIAN	-0.743	0.437	1.598*	0.814	-0.930	0.561	-0.830	1.024
HISPANIC	0.002	0.072	1.049*	0.390	0.027	0.120	-0.239	0.148
METRO	-0.026	0.090	-0.980*	0.399	-0.464*	0.119	1.182*	0.105
NE_REG	0.302	0.209	0.428	0.562	-0.206	0.225	1.149*	0.372
MA_REG	0.281	0.186	-1.027*	0.449	-0.047	0.211	0.698*	0.298
SA_REG	-0.109	0.155	1.111*	0.450	-0.539*	0.190	0.078	0.281
ESC_REG	0.447	0.238	3.290*	0.791	-0.805*	0.326	0.830	0.519
ENC_REG	0.228	0.153	-2.788*	0.546	-0.094	0.178	1.428*	0.294
WNC_REG	0.630*	0.170	-3.973*	1.031	-0.073	0.229	2.791*	0.383
WSC_REG	0.397*	0.146	-1.394*	0.408	-0.150	0.175	1.363*	0.363
MNT_REG	0.053	0.158	-1.586*	0.553	-0.156	0.185	0.389	0.289
JANUARY	1.018*	0.060	1.214*	0.458	0.819*	0.118	0.829*	0.172
FEBRUARY	0.025	0.058	0.187	0.479	0.056	0.099	0.018	0.154
MARCH	0.532*	0.061	0.568	0.397	0.485*	0.111	0.388*	0.165
APRIL	-0.026	0.059	0.175	0.359	-0.030	0.098	-0.051	0.160
MAY	-0.089	0.057	0.201	0.424	-0.094	0.098	-0.119	0.159
JUNE	-0.110*	0.057	0.146	0.385	-0.147	0.094	-0.147	0.153
JULY	0.299*	0.051	0.411	0.341	0.200*	0.089	0.196	0.146
AUGUST	1.064*	0.056	0.877*	0.382	0.810*	0.095	0.801*	0.156
SEPTEMBER	0.018	0.052	0.138	0.367	0.012	0.090	-0.012	0.151
OCTOBER	0.030	0.053	0.332	0.341	-0.001	0.086	0.076	0.123
NOVEMBER	-0.039	0.048	0.165	0.318	-0.055	0.091	0.035	0.151
USE_COUPON	0.770*	0.028	3.508*	0.181	1.442*	0.038	2.261*	0.062
σ_1	1.749*	0.001	0.917*	0.001	1.336*	0.001	1.013*	0.001
σ_2	2.432*	0.026	1.162*	0.013	1.937*	0.019	1.782*	0.021
ϕ	-0.004	0.002	-0.013*	0.004	-0.002	0.001	-0.001	0.002
ρ	0.272*	0.001	0.496*	0.001	0.337*	0.001	0.335*	0.001
Log Likelihood	-180,491		-109,841		-156,563		-126,178	

Note: An asterisk (*) denotes significance at the 5% level. Second-stage standard errors are corrected Murphy and Topel asymptotic standard errors (Greene, p. 142).

[a] Advertising expenditures are included as a quadratic polynomial distributed lag (PDL) with endpoints restricted to zero. The coefficient represents the estimated lag-weighted PDL parameter estimate, λ_2 (see text for a detailed description).

Table A3. Maximum-Likelihood First-Stage Probit Parameter Estimates, by Cheese Product Type

	Total Cheese		American		Mozzarella		Processed		Other	
Variable	Esti-mate	Std. Error	Esti-mate	Std. Error	Esti-mate	Std. Error	Esti-mate	Std. Error	Esti-mate	Std. Error
Intercept	1.524*	0.109	0.603*	0.104	0.377*	0.111	1.232*	0.099	0.383*	0.104
ln(*NET_PRICE*)	-0.370*	0.007	-0.698*	0.007	-0.427*	0.008	-0.576*	0.005	-0.575*	0.004
ln(*INCOME*)	0.070*	0.003	0.034*	0.003	0.057*	0.003	-0.027*	0.003	0.146*	0.003
HH_SIZE^{-1}	-0.693*	0.008	-0.587*	0.008	-0.597*	0.011	-0.681*	0.008	-0.435*	0.008
FH_AGE	-0.003*	0.000	-0.003*	0.000	-0.011*	0.000	-0.002*	0.000	0.000	0.000
PR_LT13	0.394*	0.015	0.193*	0.012	0.352*	0.016	0.225*	0.012	0.294*	0.012
PR_1317	0.343*	0.018	0.207*	0.015	0.314*	0.019	0.344*	0.015	0.263*	0.016
PR_GT65	0.000	0.007	0.018*	0.006	-0.024*	0.009	-0.048*	0.006	0.010	0.007
USCHZADV PDL [a]	0.015	0.016	-0.067*	0.015	0.032*	0.016	0.052*	0.015	0.009	0.015
BRCHZADV PDL [a]	0.011	0.014	-0.007	0.014	0.013	0.014	0.040*	0.013	0.018	0.013
COLLEGE	-0.064*	0.003	-0.009*	0.003	0.071*	0.004	-0.145*	0.003	0.038*	0.003
FH_WORKS	-0.044*	0.004	-0.058*	0.004	-0.013*	0.005	-0.052*	0.004	-0.044*	0.004
YNGSNGL	0.133*	0.016	-0.089*	0.017	0.024	0.017	0.088*	0.015	0.169*	0.017
DINKS	0.129*	0.006	0.049*	0.005	-0.015*	0.007	0.089*	0.005	0.072*	0.006
BLACK	-0.414*	0.006	-0.079*	0.006	-0.465*	0.008	-0.125*	0.006	-0.659*	0.007
ASIAN	-0.702*	0.010	-0.636*	0.015	-0.372*	0.020	-0.337*	0.014	-0.527*	0.012
HISPANIC	-0.060*	0.008	-0.166*	0.006	0.040*	0.009	-0.141*	0.007	0.021*	0.007
METRO	-0.048*	0.005	-0.108*	0.004	-0.016*	0.005	-0.074*	0.004	0.118*	0.004
NE_REG	-0.027*	0.007	-0.162*	0.007	0.038*	0.009	0.029*	0.006	0.073*	0.007
MA_REG	-0.015*	0.006	-0.261*	0.006	0.174*	0.007	0.086*	0.005	0.034*	0.006
SA_REG	0.084*	0.005	-0.032*	0.005	0.001	0.007	0.229*	0.005	0.020*	0.005
ESC_REG	0.069*	0.010	0.145*	0.008	-0.175*	0.012	0.255*	0.009	-0.129*	0.010
ENC_REG	0.010	0.006	-0.018*	0.005	0.017*	0.007	0.211*	0.005	-0.054*	0.006
WNC_REG	-0.128*	0.007	-0.215*	0.007	-0.071*	0.009	0.045*	0.007	-0.114*	0.006
WSC_REG	0.107*	0.006	0.015*	0.006	-0.107*	0.008	0.381*	0.005	-0.106*	0.006
MNT_REG	-0.069*	0.006	-0.037*	0.006	-0.060*	0.008	0.086*	0.006	-0.038*	0.006
JANUARY	-0.097*	0.025	-0.065*	0.025	0.050	0.027	-0.044	0.024	-0.137*	0.023
FEBRUARY	-0.116*	0.025	-0.096*	0.025	0.042	0.027	-0.097*	0.025	-0.153*	0.023
MARCH	0.073*	0.026	-0.010	0.026	0.167*	0.028	0.054*	0.025	0.028	0.023
APRIL	-0.130*	0.026	-0.134*	0.027	0.008	0.030	-0.083*	0.027	-0.155*	0.025
MAY	-0.160*	0.027	-0.184*	0.028	-0.021	0.031	-0.083*	0.027	-0.174*	0.026
JUNE	0.008	0.028	-0.064*	0.028	0.063*	0.031	0.048	0.027	-0.061*	0.026
JULY	-0.161*	0.024	-0.181*	0.025	-0.048	0.028	-0.095*	0.024	-0.186*	0.023
AUGUST	-0.017	0.024	-0.040	0.024	0.081*	0.027	0.020	0.023	-0.064*	0.022
SEPTEMBER	-0.172*	0.023	-0.162*	0.023	0.019	0.026	-0.131*	0.023	-0.208*	0.022
OCTOBER	-0.150*	0.022	-0.123*	0.024	-0.003	0.026	-0.104*	0.023	-0.169*	0.021
NOVEMBER	0.119*	0.024	0.089*	0.023	0.111*	0.026	0.044	0.023	0.088*	0.021
Log Likelihood	-51,174		-54,197		-39,904		-57,388		-58,736	

Note: An asterisk (*) denotes significance at the 5% level.

[a] Advertising expenditures are included as a quadratic polynomial distributed lag (PDL) with endpoints restricted to zero. The coefficient represents the estimated lag-weighted PDL parameter estimate, λ_2 (see text for a detailed description).

Table A4. Maximum-Likelihood Second-Stage Parameter Estimates, by Cheese Product Type

Variable	Total Cheese Estimate	Total Cheese Std. Error	American Estimate	American Std. Error	Mozzarella Estimate	Mozzarella Std. Error	Processed Estimate	Processed Std. Error	Other Estimate	Other Std. Error
Intercept	5.140*	0.433	5.497*	0.530	14.593*	1.506	8.222*	0.773	0.638	0.379
ln(*NET_PRICE*)	-1.506*	0.013	-1.564*	0.020	-7.535*	0.132	-3.573*	0.033	-1.660*	0.017
ln(*INCOME*)	0.120*	0.037	0.047	0.048	0.117	0.104	-0.017	0.067	0.161*	0.030
HH_SIZE^{-1}	-1.644*	0.102	-1.106*	0.136	-1.323*	0.321	-1.649*	0.184	-0.637*	0.089
FH_AGE	-0.020*	0.003	-0.010*	0.004	-0.052*	0.008	-0.021*	0.005	-0.003	0.002
PR_LT13	0.671*	0.141	0.247	0.184	3.025*	0.370	0.643*	0.251	0.382*	0.126
PR_1317	0.966*	0.159	0.328	0.213	2.241*	0.403	1.038*	0.274	0.522*	0.148
PR_GT65	-0.182	0.099	-0.187	0.104	-0.110	0.331	-0.188	0.187	-0.067	0.072
USCHZADV PDL [a]	-0.339*	0.057	0.036	0.064	-0.292	0.204	-0.187	0.102	-0.573*	0.052
BRCHZADV PDL [a]	-0.074	0.042	-0.116*	0.044	-0.015	0.150	-0.015	0.073	-0.125*	0.035
COLLEGE	-0.004	0.052	-0.002	0.066	0.162	0.134	-0.179	0.096	0.021	0.041
FH_WORKS	-0.149*	0.038	-0.060	0.049	-0.217*	0.100	-0.260*	0.062	0.006	0.035
YNGSNGL	0.060	0.257	-0.098	0.382	-0.142	0.700	0.093	0.326	-0.015	0.349
DINKS	0.023	0.063	-0.087	0.080	0.070	0.176	-0.033	0.097	0.075	0.050
BLACK	-0.697*	0.143	-0.179	0.168	-1.672*	0.363	0.018	0.214	-0.669*	0.160
ASIAN	-0.953*	0.232	-1.330*	0.319	-1.614*	0.452	-0.255	0.478	-0.323	0.195
HISPANIC	0.017	0.104	0.135	0.101	0.471	0.311	-0.320	0.176	0.080	0.076
METRO	-0.092	0.080	-0.317*	0.102	-0.086	0.204	-0.422*	0.139	0.228*	0.072
NE_REG	-0.341*	0.144	-1.213*	0.198	-0.858*	0.287	-0.259	0.323	0.033	0.093
MA_REG	-0.344*	0.124	-1.276*	0.159	-0.352	0.242	0.103	0.254	-0.068	0.077
SA_REG	-0.351*	0.114	-1.008*	0.125	-1.129*	0.243	0.214	0.236	-0.116	0.069
ESC_REG	-0.333	0.195	-0.448*	0.214	-1.417*	0.551	0.399	0.384	-0.392*	0.164
ENC_REG	-0.438*	0.131	-0.907*	0.145	-1.193*	0.280	0.281	0.254	-0.331*	0.093
WNC_REG	-0.787*	0.151	-1.227*	0.181	-2.007*	0.371	-0.158	0.302	-0.528*	0.106
WSC_REG	-0.139	0.120	-0.764*	0.128	-1.199*	0.250	0.894*	0.237	-0.361*	0.092
MNT_REG	-0.061	0.124	-0.560*	0.133	-0.913*	0.278	0.397	0.248	-0.025	0.082
JANUARY	-0.510*	0.069	-0.135*	0.067	-0.255	0.291	-0.476*	0.115	-0.489*	0.057
FEBRUARY	-0.449*	0.073	0.035	0.074	0.068	0.275	-0.326*	0.137	-0.475*	0.063
MARCH	-0.356*	0.071	0.175*	0.081	-0.478	0.312	-0.260	0.133	-0.578*	0.060
APRIL	-0.827*	0.076	-0.162*	0.082	-0.311	0.318	-0.485*	0.156	-0.861*	0.065
MAY	-0.769*	0.078	-0.238*	0.084	-0.255	0.328	-0.410*	0.152	-0.803*	0.063
JUNE	-0.560*	0.080	0.218*	0.090	-0.198	0.314	-0.515*	0.147	-0.859*	0.063
JULY	-0.752*	0.075	-0.302*	0.076	-0.275	0.307	-0.484*	0.142	-0.764*	0.064
AUGUST	-0.373*	0.071	-0.113	0.075	-0.137	0.313	-0.342*	0.128	-0.588*	0.059
SEPTEMBER	-0.633*	0.070	-0.059	0.075	-0.050	0.259	-0.103	0.130	-0.643*	0.060
OCTOBER	-0.315*	0.072	-0.238*	0.067	-0.220	0.293	-0.250*	0.119	-0.250*	0.069
NOVEMBER	-0.169*	0.067	0.033	0.070	0.049	0.276	0.331*	0.133	-0.415*	0.057
USE_COUPON	1.934*	0.028	3.316*	0.047	9.202*	0.205	4.841*	0.070	2.252*	0.032
σ_1	1.659*	0.001	0.700*	0.000	0.537*	0.001	0.977*	0.000	0.791*	0.000
σ_2	1.073*	0.011	0.452*	0.004	0.246*	0.002	0.607*	0.007	0.448*	0.004
ϕ	-0.001	0.004	-0.008	0.006	0.076*	0.024	0.019*	0.006	0.023*	0.007
ρ	0.054*	0.002	0.082*	0.001	0.064*	0.001	0.017*	0.002	0.088*	0.001
Log Likelihood	-179,654		-99,671		-74,663		-130,002		-111,234	

Note: An asterisk (*) denotes significance at the 5% level. Second-stage standard errors are corrected Murphy and Topel asymptotic standard errors (Greene, p. 142).

[a] Advertising expenditures are included as a quadratic polynomial distributed lag (PDL) with endpoints restricted to zero. The coefficient represents the estimated lag-weighted PDL parameter estimate, λ_2 (see text for a detailed description).