Dynamics of Advertising and Demand for Fluid Milk in the United States: An Incomplete Demand Approach

Rejeana M. Gvillo*
Oral Capps, Jr.*
Senarath Dharmasena*

*Agribusiness, Food, and Consumer Economics Research Center (AFCERC),
Texas A&M University
Department of Agricultural Economics
600 John Kimbrough Blvd Ste. 371
2124 TAMU
College Station, TX 77843-2124

Emails: rgvillo@tamu.edu; ocapps@tamu.edu; sdharmasena@tamu.edu;

Phone: (979) 845-5911

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Abstract

Fluid milk consumption has been on a decline in the United States for several years. The check off program funded by producers and processors of fluid milk provides generic advertising targeted at fluid milk consumption. Exploring how generic advertising affects fluid milk type consumption delineated by milk fat type is examined by incorporating a polynomial distributed lag advertising variable into an incomplete demand system. Seemingly unrelated regression results indicate that generic advertising indeed affects milk type consumption differently. The optimal advertising lag is five months. Whole milk has no significant advertising effects while low-fat and skim milks have positive, significant effects.

Keywords: Fluid Milk, Generic Advertising, PDL, Incomplete System, SUR

JEL Classification: D11, D12

[*] Rejeana Gvillo is a PhD candidate in the Department of Agricultural Economics at Texas A&M University. Rejeana Gvillo, Oral Capps, Jr., and Senarath Dharmasena are affiliates of AFCERC at Texas A&M University. Oral Capps, Jr. is co-director of AFCERC.

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Introduction

Per capita dairy product consumption and milk supply have been on a rise in the United States though per capita fluid milk consumption has been on a decline for more than a decade (ERS, 2013; USCB, 2012, 2010, 2001). In 2000, fluid milk per capita consumption was approximately 21 gallons per year. By 2011, that total dropped to 17.8 gallons (a 14.9 % drop) per year (Nielsen Scantrak, 2012; USCB, 2012, 2010, 2001). Milk advertising funds decreased as well in the same period from $321 million to $240 million (a 25.2% decline) per year (Dairy Management Inc, 2013; MilkPeP, 2013; Qualified Programs, 2013). Previous work has explored the effect of advertising on fluid milk consumption in the United States, however, this paper centers attention on analyzing such effects on fluid milk consumption delineated by milk fat types, namely, whole, low-fat, and skim milks.

Per capita fluid milk consumption has been on a decline, though total dairy product consumption has been on a rise (ERS 2013). While milk leaves the farm to become part of a plethora of dairy products, fluid milk processors are likely curious as to why total fluid milk consumption is falling. One reason may be related to health concerns. Multiple studies have been conducted in recent years relating the correlation between the rise in obesity and milk consumption (Berkey *et al.* 2005; Wiley 2010; Mozaffarian *et al*. 2011; Chen *et al*. 2012), though findings are mixed. Further, Women, Infants, and Children's (WIC) requirements (2012) were recently modified to only allow parents whose child(ren) is(are)less than two years as being eligible to use WIC to purchase *whole* milk.

Milk is a unique commodity because it offers four types of milk to analyze, all with different milk fat contents, similar prices, and a generic advertising campaign which is not designed to target specific milk advertising strategies. Previous studies have analyzed generic advertising's effect on milk consumption. While different methods of modeling advertising have

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been used, results are rather similar. Kaiser and Reberte (1996) used a log-log model with eleven monthly advertising lags. Though results were confined to New York City, long term advertising elasticities were positive and significant ranging from 0.16 (whole milk) to 0.19 (low-fat milk). In a similar model specification, Kinnucan and Forker (1986) examined monthly interactions with advertising strategies finding that the cumulative effect of milk advertising on sales was the greatest in months when consumers have the strongest preference for milk. These results, too, were confined to New York City. Another study, conducted by Capps and Schmitz (1991), used a log-log model modified by a polynomial distributed lag to capture advertising effects of milk in Texas, finding a long run advertising elasticity effect of 0.0075 for fluid milk.

Though these findings have similar results, implications can only be utilized in the specific areas each particular study catered to or for all fluid milk. In addition, consumption behavior within the United States (US) population has changed, particularly where milk is concerned. To better address this issue, using recent data representative of the entire US may be more appropriate and applicable. Further, addressing the key issue of whether each milk type has the same advertising lag and effect is necessary to model advertising effects appropriately for each milk type. For this study, we have the following objectives: (1) assess optimal lag lengths for generic advertising for each milk type, (2) estimate the long- and short-term effects generic advertising has on milk type consumption through a polynomial distributed lag, (3) estimate income effects, and (4) estimate advertising and income elasticities.

Methodology

Though complete demand systems have been used to model advertising's effects on various products, one key issue that exists within the complete demand system framework is singularity. Due to the sum of expenditures equaling the income of the system, estimation can only occur for N-1 equations, using adding up to recover the final equation. Thus, for relationships that may seem transparent, such as advertising effects, the system's framework may force at least one negative relationship for the goods within the system. For instance, Kinnucan *et al*. (2001) used a Rotterdam model to analyze the effects of advertising on non-alcoholic beverages, finding negative advertising effects and elasticities for a few of the beverage categories. Likewise, Zheng and Kaiser (2008), who examined similar goods as Kinnucan at el. (2001) but with an

AIDS model, also had a negative own advertising elasticity for juice. Simply stated, complete demand systems force a negative relationship with at least one variable for one good within the system.[1]

Incomplete demand systems allow a more general class of functional forms than complete demand models (LaFrance and Hanemann 1989). The added generality is due to the adding-up condition not being an equality restriction but rather an inequality restriction on the total expenditure for the goods of interest (LaFrance and Hanemann 1989). There are many forms of incomplete demand systems.[2] As von Haefen (2002) shows, the dependent variable form is flexible and may be an expenditure share, expenditure, or the actual quantity. Other than having flexibility where the dependent variable is concerned, incomplete demand system framework allows us to include income as a variable, as opposed to system expenditure. This alleviates one concern and provides a desired outcome. Endogeneity of expenditure is not an issue as income rather than system expenditure is used. Hence, we can generate income elasticities as compared to expenditure elasticities. Incomplete demand systems typically incorporate quantity, price, and income. A simple example of an equation is (Lafrance 1985):

$$x_i = \alpha_i(q) + \sum_{k=1}^{n} \beta_{ik} p_k + \gamma_i y, \quad \forall\, i \tag{1}$$

where *x* is the Marshaillian demand for good *i*, *q* is the quantity of good *i*, *p* the price of good *i*, and *y* is income. This formula can be in log-log form, providing the elasticities as the estimates themselves. This general model was selected to analyze three fluid milk types, delineated by fat content including whole, low-fat (two-percent and one-percent), and skim milks. Further, we utilize Zellner's (1962) seemingly unrelated regression technique (SUR) by estimating all of the equations simultaneously. This is appealing due to possible correlation across the errors in different equations which can provide links that can be exploited during estimation (Wooldridge 2010).

Due to milk's decrease in per capita consumption (ERS 2013), we are interested in the effects generic advertising has on milk. Specifically, we intend to capture advertising effects by incorporating a polynomial distributed lag (PDL) (Almon 1965) advertising variable, whose lag

[1] There are various `tricks' that can be done to fool the additivity constraint. See the previous chapter.
[2] To see multiple variations of incomplete demand models, see Appendix I.

corresponds to each milk type. A polynomial of degree two can be used to recover time specific advertising effects. These effects then can be summed to provide long run advertising effects. Optimal advertising lag lengths have been explored for many products including milk (Capps and Schmitz 1991; Kinnucan 1986; Kinnucan and Forker 1986; Kaiser and Reberte 1996). The number of optimal advertising lags for each of these papers differs slightly ranging from six months (Kinnucan 1986) to one year (Capps and Schmitz 1991). Clarke (1976) noted that 90% of the cumulative advertising effect of advertising on sales of mature, frequently purchased, low-priced items occurs within three to nine months of the advertisement. Following previous research and Clarke's (1976) assessment, lag lengths were searched varying from two months to 14 months. The optimal lag length for each milk type was chosen based on the Schwarz's Bayesian Information Criterion (SBIC) and overall model fit. Our modified incomplete demand model now takes this form:

$$\ln q_{it} = \beta_{i1} \ln q_{i,t-1} + \beta_{i2} \ln inc_t + \sum_{k=0} \theta_{ik} \ln Adv_{t-k} + \sum_{j} \alpha_{ij} \ln p_{jt} + \sum_{m} \pi_i m_{mt} \qquad (2)$$

where q_{it} is the per capita consumption (in gallons) of milk type `*i*' during month `*t*', *p* is the price for each milk type *i* at time *t*, *inc* is household income, *Adv* is the polynomial distributed lag advertising variable, and *m* is a dummy variable corresponding to the month of the observation. The optimal PDL advertising lag was five for total fluid milk and for each individual milk type.

Because of such a large decrease in the quantity of milk consumed, particularly whole milk, there may be improved opportunities for milk advertising agencies to advertise specifically for each milk type, rather than for fluid milk in general. If the same pool of advertising funds in fact affects milk types differently, advertising strategies may be adjusted to compensate for milk types whose generic campaign does not affect consumption as much as other milk types. Further, there may be separate advertising time (lag) effects for each milk type, intensifying the need for campaign adjustments.

Data

The data used for this study correspond to milk consumption and prices from January 2000 to December 2011 and is representative of the entire US. Milk prices, from Neilsen Scantrak data, are deflated using the Consumer Price Index (CPI) (BLS 2014). Likewise, advertising expenditures were deflated by the CPI, and gathered from Dairy Management Inc, MilkPeP, and Qualified Programs. The advertising expenditures are reported quarterly; thus, we create monthly advertising expenditures, and then adjust those for seasonality using SAS v9 `Proc IM' command. Quantities were reported in millions of pounds (ERS 2013; Neilsen 2013) and then converted to per capita consumption using Census population estimates (USCB 2012, 2010, 2001) and a conversion factor of 8.6 pounds of milk per gallon (Dairy Facts 2008). Median per capita income was retrieved from the Census (USCB 2013). Table 1 provides the summary statistics of the variables used.

Table 1: Summary Statistics

Variable	Units of Measurement	Mean	Std. Dev.	Minimum	Maximum
Advertising*	US$	11,034,110	1,992,288	8,144,160	16,467,014
CPI	Price Index	198.25	17.29	168.8	226.89
Income/	US$	52,876.75	1,322.82	50,054.00	54,841.00
Whole Price*	US$/gal	1.53	0.12	1.25	1.86
2% Price*	US$/gal	1.47	0.12	1.21	1.79
1% Price*	US$/gal	1.46	0.12	1.2	1.76
Skim Price*	US$/gal	1.44	0.11	1.17	1.71
Fluid Milk^	Gallons/month	1.61	0.09	1.41	1.87
Whole Milk^	Gallons/month	0.54	0.07	0.41	0.67
2% Milk^	Gallons/month	0.59	0.03	0.53	0.66
1% Milk^	Gallons/month	0.22	0.02	0.17	0.26
Skim Milk^	Gallons/month	0.26	0.01	0.23	0.32

/: in 2011 dollars ; * Adjusted for inflation using CPI; ^: per capita consumption;

The summary statistics provide us with some useful information. We see that average monthly advertising expenditures exceed 11 million dollars. Milk prices (deflated) range from $1.53 – $1.44, with the higher prices corresponding to the higher milk fat content products. We can also see that total per capita fluid milk consumption is about one and a half gallons per month. Further, two percent milk is consumed the most, with whole milk being a close second.

Collinearity among prices is a concern. We can still obtain estimation results when there exists high collinearity among variables; however, estimates may have the wrong signs, be sensitive to slight changes in the data or model specification, or may not yield statistically significant results for theoretically important explanatory variables (Hill and Adkins 2001). Previous work on dairy milk demand by Kaiser and Reberte (1996) mentioned this problem. To mitigate collinearity price issues, we create a price ratio. For each milk type `*i*', we use the following:

$$\text{Price Ratio}_i = \frac{p_i}{\left(\frac{\sum_{j \neq i} p_j q_j}{\sum_{j \neq i} q_j}\right)} \equiv \frac{p_i * \sum_{j \neq i} q_j}{\sum_{j \neq i} p_j q_j} \tag{3}$$

Several pieces of literature within the fluid milk sector have combined milk types to represent 'low-fat' milk (see literature above). In other words, two-percent and one-percent milks are combined to create a low-fat category. Quantities are simply added while price is an index calculated such as:

$$p_{2\%,1\%} = \frac{p_{2\%} * q_{2\%} + p_{1\%} * q_{1\%}}{q_{2\%} + q_{1\%}} \tag{4}$$

Due to combining two percent and one percent, we have three milk types and three equations to estimate. The three equations, though each has its own set of parameter estimates, are likely related through prices and consumption. Employing a seemingly unrelated regression method will help address this issue. Serial correlation of the error terms for each individual equation was of concern. The final equation for each milk type was corrected for serial correlation using the specific equation's serial correlation coefficient such as:

$$\begin{aligned} \ln q_{it} &= \rho_i * \ln q_{i,t-1} + \beta_{i1} \ln q_{i,t-1} + \beta_{i2} \ln inc_t + \sum_{k=0} \theta_{ik} \ln Adv_{t-k} + \ln pr_{it} + \sum_m \pi_i m_{mt} \\ &- \rho_i * \left(\beta_{i1} \ln q_{i,t-2} + \beta_{i2} \ln inc_{t-1} + \sum_{k=0} \theta_{ik} \ln Adv_{t-k-1} + \ln pr_{i,t-1} + \sum_m \pi_i m_{m,t-1} \right) + \varepsilon_{it} \end{aligned} \tag{5}$$

where q_{it} is the per capita consumption (in gallons) of milk type `*i*' during month `*t*', *pr* is the price ratio for each milk type *i* at time *t*, *inc* is household income, *Adv* is the polynomial distributed lag advertising variable with lag five, *m* is a dummy variable corresponding to the month of the observation, and ρ represents each equations' AR(*p*) serial correlation term.

Single Equation Estimation

First, we estimate all fluid milk and the milk types separately. Then, with SUR estimation in Stata v12.1, we estimate three equations together for whole, low-fat, and skim milks. Results for single equation estimations are presented first.

Table 2: Parameter Results for Single Equation Estimation

	All Fluid Milk	Whole	Low-Fat	Skim
AR(p)	AR(0)	AR(1,3)	AR(1)	AR(1,3)
Constant	-1.579	-1.503	-1.299	-4.092***
	(1.170)	(1.290)	(1.461)	(0.999)
Quantity Lag	0.059	0.946***	0.134	0.667***
	(0.091)	(0.031)	(0.091)	(0.064)
Price Ratio/	-0.069***	-0.043	-0.064*	-0.009
	(0.021)	(0.130)	(0.035)	(0.073)
Income	0.138	0.071	0.038	0.298***
	(0.092)	(0.092)	(0.162)	(0.089)
Advertising	-0.001*	-0.001*	-0.001*	-0.001**
	(0.000)	(0.000)	(0.001)	(0.000)
January	0.014*	-0.059***	0.020**	0.033***
	(0.008)	(0.011)	(0.008)	(0.010)
February	-0.095***	-0.158***	-0.091***	-0.087***
	(0.008)	(0.009)	(0.010)	(0.009)
March	0.001	0.036***	0.012	0.062***
	(0.009)	(0.008)	(0.011)	(0.007)
April	-0.054***	-0.099***	-0.051***	-0.044***
	(0.008)	(0.010)	(0.010)	(0.010)
May	-0.038***	-0.037***	-0.032***	0.001
	(0.007)	(0.009)	(0.010)	(0.009)
June	-0.082***	-0.073***	-0.092***	-0.059***
	(0.007)	(0.009)	(0.010)	(0.008)
July	-0.055***	-0.021**	-0.060***	-0.008
	(0.008)	(0.009)	(0.011)	(0.009)
August	-0.021***	-0.033***	-0.016	0.017*
	(0.007)	(0.010)	(0.010)	(0.009)
September	-0.040***	-0.089***	-0.027***	-0.016**
	(0.007)	(0.008)	(0.009)	(0.007)
October	-0.006	-0.014	0.006	0.016*
	(0.007)	(0.009)	(0.009)	(0.008)
November	-0.033***	-0.068***	-0.029***	-0.037***
	(0.007)	(0.011)	(0.008)	(0.010)
Trend	-0.001***	--	0.001***	--
	(0.000)	--	(0.000)	--
R-Squared	0.9038	0.9818	0.7811	0.8742
Observations	139	136	138	136

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1
/: For low-fat milk, the ratio is as described in equation (4); for the other types, the price ratio is as described in equation (3).

Results for all fluid milk indicate that over time, total fluid milk consumption has been on a significant decline (see trend). Seasonality is captured using monthly dummies, and we see that most months have lower total milk consumption when compared to December. Income, though not significant, indicates that milk is a necessity good; this coincides with Capps and Schmitz's (1991) analysis of fluid milk consumption in Texas, though their income coefficient was significant. Our optimal advertising lag length was a five lag polynomial distributed lag of degree two. Compared to Capps and Schmitz (1991) and Kaiser and Reberte (1996), our advertising lag length is short. However, our advertising lag length is similar to that of Clarke (1976) and Kinnucan (1986).

For the individual milk type equations, results resemble that of total fluid milk. A trend variable was included in the low-fat milk equation to capture the increase in purchases of low-fat milk over this time span. In fact, it is positive and significant, suggesting that even though total fluid milk consumption is on a decline, low-fat milk consumption has been increasing. We see that a quantity lag positively and significantly affects both whole and skim milks, indicating significant habitual purchasing behavior. Though the price ratios were negative for all milk types, only the low-fat milk ratio had a significant effect. The estimated coefficient for advertising was negative; however, this coefficient is the estimated phi resulting from imposing end point restrictions (heads and tails) on the PDL. To recover the total value of each advertising lag, or theta, we use simple algebra and substitution. The following formula was used in calculating each theta:

$$\theta_{ij} = \varphi_0 + i * \varphi_1 + i^2 * \varphi_2 \qquad \text{for i} = 0, \ldots 5, \forall \text{ j} \tag{5}$$

This formula builds a symmetric relationship, which is supported by the recovered values below.

Table 3: Recovered Thetas from Individual Equations

	All Fluid Milk	Whole	Low-Fat	Skim
Theta 0	0.004**	0.004**	0.008**	0.003**
	(0.002)	(0.002)	(0.004)	(0.002)
Theta 1	0.007**	0.006**	0.014**	0.005**
	(0.004)	(0.004)	(0.007)	(0.003)
Theta 2	0.008**	0.008**	0.016**	0.006**
	(0.005)	(0.004)	(0.009)	(0.003)
Theta 3	0.008**	0.008**	0.016**	0.006**
	(0.005)	(0.004)	(0.009)	(0.003)
Theta 4	0.007**	0.006**	0.014**	0.005**
	(0.004)	(0.004)	(0.007)	(0.003)
Theta 5	0.004**	0.004**	0.008**	0.003**
	(0.002)	(0.002)	(0.004)	(0.002)

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Total fluid milk and individual milk types have positive, significant total advertising effects for each time period from current to five lags. Low-fat milk has the largest magnitude with skim having the highest significance. Summing all of the thetas for each milk types allows us to see the long run effects of advertising. Those results are presented below.

Table 4: Advertising Effects from Individual Equations

	All Fluid Milk	Whole	Low-Fat	Skim
Short Run Advertising	0.004**	0.004**	0.008**	0.003**
	(0.002)	(0.002)	(0.004)	(0.002)
Long Run Advertising	0.039**	0.036**	0.077**	0.030**
	(0.022)	(0.020)	(0.041)	(0.014)

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The short run and long run advertising effects tell us the contemporaneous and total advertising effect. Long term effects are greatest for low-fat milk consumption. Though advertising is generic, it affects milk types differently; there is a two-fold increase in effects for low-fat milks when compared to both whole and skim milks. Because the equation was in log-log form, these resulting values are also elasticities. For a 10% increase in advertising expenditures, we see a 0.39% increase in total milk consumption, over a five month lag.

Seemingly Unrelated Regression Estimation

After estimating each equation individually, we estimated the equations using the `sureg' command in Stata which is the Seemingly Unrelated Regression technique (Zellner, 1962). Each equation was adjusted for serial correlation, specific to that equation (not the system). Parameter results for equation 5 are presented below:

Table 5: Parameter Results from SUR Equation

	Whole	Low-Fat	Skim
AR(p)	AR(1,2)	AR(1)	AR(1,2)
Constant	1.383	-1.696*	-3.226***
	(0.898)	(1.018)	(0.756)
Quantity Lag	1.012***	0.739***	0.882***
	(0.009)	(0.040)	(0.019)
Price Ratio/	-0.047	-0.009	-0.027
	(0.041)	(0.010)	(0.019)
Income	-0.051	0.058	0.123***
	(0.035)	(0.067)	(0.035)
Advertising	-0.000	-0.001**	-0.000*
	(0.000)	(0.000)	(0.000)
January	-0.063***	0.005	0.028***
	(0.012)	(0.010)	(0.009)
February	-0.162***	-0.119***	-0.100***
	(0.010)	(0.008)	(0.008)
March	0.040***	0.050***	0.069***
	(0.008)	(0.009)	(0.007)
April	-0.101***	-0.067***	-0.055***
	(0.011)	(0.009)	(0.008)
May	-0.035***	-0.018**	-0.000
	(0.010)	(0.009)	(0.008)
June	-0.072***	-0.085***	-0.063***
	(0.009)	(0.009)	(0.008)
July	-0.019*	-0.016*	-0.001
	(0.010)	(0.009)	(0.008)
August	-0.033***	0.011	0.020**
	(0.011)	(0.009)	(0.008)
September	-0.090***	-0.028***	-0.020***
	(0.008)	(0.009)	(0.007)
October	-0.013	0.007	0.014*
	(0.010)	(0.008)	(0.008)
November	-0.068***	-0.047***	-0.045***
	(0.012)	(0.010)	(0.009)
Trend	---	0.000***	---
	---	(0.000)	---
Observations	137	137	137

Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1
/: For low-fat milk, the ratio is as described in equation (); for the other types, the price ratio is as described in equation ().

The standard errors of the SUR equation results are smaller than that of the single equation estimation, and coefficient estimates are asymptotically more efficient (Zellner 1962). Parameter estimates from SUR estimation will not be the same as those from the single equation estimation due to each equation having different explanatory variables and the error terms being correlated.

Contrary to previous results, income has a negative sign for whole milk consumption, though it is not statistically different from zero. All equations have negative price ratios, though none are significant. Advertising effects are significant for both low-fat and skim milks. Habit formation, captured by the quantity lag, increased for all three milk categories when compared to the single equation estimations. Milk consumption for the previous month significantly affects the quantity consumed for the next month.

Seasonality, captured by months, is similar when compared to the single equation estimation. In general, consumption during most months is lower when compared to December. Interestingly, whole milk consumption significantly drops during the month of January while skim milk consumption significantly increases when compared to December, perhaps relating to New Year's resolutions and persons trying to reduce calorie consumption. Milk consumption is high in March relative to all other months. This could be due to spring break vacations within schools and parents providing more milk at home for children during that time.

Thetas are recovered from the advertising variable as discussed previously. Results are presented below.

Table 6: Recovered Thetas from SUR Estimation

	Whole	Low-Fat	Skim
Theta 0	0.000	0.004***	0.001**
	(0.001)	(0.002)	(0.001)
Theta 1	0.000	0.007***	0.002**
	(0.001)	(0.003)	(0.001)
Theta 2	0.000	0.008***	0.002**
	(0.001)	(0.003)	(0.001)
Theta 3	0.000	0.008***	0.002**
	(0.001)	(0.003)	(0.001)
Theta 4	0.000	0.007***	0.002**

	(0.001)	(0.003)	(0.001)
Theta 5	0.000	0.004***	0.001**
	(0.001)	(0.002)	(0.001)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The single equation estimation resulted in significant advertising effects for all milk types; with simultaneous equation estimation, we see there are no significant effects of advertising for whole milk. This further supports the idea that though advertising is generic for all fluid milk, it has different effects for specific milk types. As with the single equation estimation, low-fat milk's advertising effects are higher in magnitude that that of skim milk, and in this case, are also more significant.

Table 7: Advertising Effects from SUR Estimation

	Whole	Low-Fat	Skim
Short Run Advertising	0.000	0.004***	0.001**
	(0.001)	(0.002)	(0.001)
Long Run Advertising	0.001	0.036***	0.009**
	(0.007)	(0.014)	(0.005)

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Long run advertising effects are smaller in magnitude for the simultaneous estimation compared to the single equation estimation. If advertising expenditures were to increase by 10%, we see that low-fat milk consumption would increase by about 0.36%, compared to more than 0.7% for the single equation estimation. Further, there is little effect for whole milk, and its advertising effects are not different from zero. This aligns somewhat with the data in that though advertising significantly affects low-fat and skim milk consumption, whole milk is not affected, hence its decreasing consumption.

Conclusion

This paper measures the effects of a polynomial distributed lag advertising variable on fluid milk types using an incomplete demand system approach. We analyze advertising effects on per capita consumption for three milk types including whole milk, low-fat milk (two-percent and one-percent milk), and skim milk, mitigating collinearity issues among prices by using a price index. Single equation estimation for total fluid milk and each milk type is conducted followed by seemingly unrelated regression equation estimation for three milk types. The optimal advertising lag length for all milk types is five months.

When estimating using a SUR, results suggest that long run advertising effects vary across milk types. For low-fat milk, advertising effects are the largest in magnitude as well as the most significant. Generic advertising had no effect on whole milk consumption. Advertising elasticities suggest that if advertising expenditures increase, both low-fat and skim milk consumption will increase, skim milk increasing only moderately. Both low-fat and skim milks are necessities while no income effect was found for whole milk. Seasonality suggests that milk consumption peaks during March and December for all milk types.

Due to the different advertising effects for whole, low-fat, and skim milks, advertising expenditures may be spent accordingly to cater to those consumption differences. For instance, since generic advertising does not affect whole milk consumption, perhaps a different strategy could focus on whole milk while the generic advertising (or low-fat advertising) caters to two-percent, one-percent, and skim milks. Further, such campaigns may be able to increase consumption of specific milk types.

While there are no separate advertising expenditures for milk types, future research should examine other similar products/commodities and their advertising effects. For instance, Pima cotton and `regular' cotton have separate advertising campaigns; perhaps examining if any variation exists in advertising effects between the two products would provide insight for other commodity advertising campaigns. Finding ways to accommodate high collinearity among prices is also of interest. Though complete demand systems' structures mitigate price collinearity through specific restrictions, such restrictions are not implemented in the incomplete demand systems approach. First differencing can reduce multicollinearity, but Burt (1987) points out that first differencing used in this manner is a `fallacy.' Though price indexes rid the issue of multicollinearity, it comes at a cost as we are no longer able to interpret cross price effects.

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