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On the Estimation of Advertising Effects for Branded Products: An Application to Spaghetti Sauces

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ABSTRACT

Using IRI Infoscan data pertaining to six types of spaghetti sauces and employing an extension of the demand systems framework developed by Duffy, estimates are obtained of own-price, cross-price, and total expenditure elasticities as well as own- and cross-product advertising elasticities. We augment the Duffy model through the use of a polynomial inverse lag mechanism to deal with the carryover effects of advertising. We also account for the impacts of features in newspaper fliers, in-store displays, and coupons. Advertising efforts by industry leaders in spaghetti sauce produce positive own-advertising elasticities (ranging from .000058 to .0168) and negative cross-advertising elasticities (ranging from −.000003 to −.0094). Own-price elasticities are in the elastic range, and nearly all compensated cross-price effects are positive, indicative of Hicksian substitutes.

Key Words: advertising effects, demand systems, IRI Infoscan data, polynomial inverse lag, Rotterdam model.

Most studies that have investigated the impact of advertising (either generic or branded) on sales of products have relied on single-equation modeling approaches. However, results obtained using single-equation models may not satisfy integrability conditions, and therefore may not be consistent with demand theory. Further, Lee, Brown, and Fairchild concluded that failure to incorporate the impact of advertising on closely related goods can lead to unreliable estimates of advertising effects. To circumvent this shortcoming, one may incorporate advertising variables into demand systems. (Studies that have considered the demand systems approach include Green; Baye, Jansen, and Lee; Cox; Duffy; Brown and Lee; Goddard and Amuah; Green, Carman, and McManus; Brester and Schroeder; and Piggott et al.) With the systems approach, it is possible to determine the relative impacts of advertising, prices, and total expenditure (or income) on sales of products while accounting for cross-commodity price and advertising effects.

With the availability of supermarket scanner data, consumer promotions have become a focal point in market response analysis (Guadagni and Little; Neslin, Henderson, and Quelch; Bawa and Shoemaker; Vanhonacker). Market-level commercial scanner databases—Neilsen Scantrack or Information Resources, Inc. (IRI) Infoscan—are appropriate to ana-

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lyze both demand and strategic interactions. As noted by Cotterill, "The availability of these new commercial scanner data sources now allows significant advances in our understanding of food marketing because one can now estimate firm and brand level as well as market or commodity demand models" (p. 126). Also, the use of regional or national data, rather than local data, allows a more comprehensive analysis of marketing questions.

In this light, using IRI Infoscan data, we attempt to measure the impacts of prices and advertising on the demand for spaghetti sauces among different brands of sauces. Attention is centered on six spaghetti sauces, in 15- to 40-ounce containers: Prego, Ragu, Classico, Hunt's, Newman's Own, and private label brands. The analysis examines the entire U.S. market using data collected by IRI from supermarkets on a weekly basis over the period of June 3, 1991 through May 31, 1992.

On the basis of this analysis, we extract own-price, cross-price, and total expenditure elasticities, as well as own- and cross-product advertising elasticities, for the six spaghetti sauces in the national market. To handle the advertising effects, we use the framework developed by Duffy for demand systems. However, we augment the Duffy model through the use of a polynomial inverse lag mechanism (Mitchell and Speaker) to deal with the carryover effects of advertising. The model of choice is the Rotterdam. This study makes a contribution by addressing the following areas of paucity within the literature: (*a*) little information currently exists pertaining to cross-advertising effects, particularly the branded variety; (*b*) only a few published studies have used IRI Infoscan data; (*c*) only a few published studies have employed the methodology developed by Duffy to consider advertising; and (*d*) no previous studies have considered a polynomial inverse lag within a demand system.

Model Development

Advertising effects have been incorporated into demand systems using the Almost Ideal Demand System (AIDS) (Green, Carman, and McManus; Piggott et al.), the Rotterdam model (Cox; Duffy; Brown and Lee; Brester and Schroeder), and the Translog model (Goddard and Amuah). Several approaches commonly are used to augment these demand systems' specifications to include advertising effects. One may assume that advertising acts solely to shift the demand for the commodities in question. In essence, this hypothesis represents an additive augmentation or *translation* of the demand system. Alternatively, one may assume that advertising affects demand elasticities. In this case, advertising acts to adjust prices and total expenditure. Essentially, this hypothesis represents a multiplicative augmentation or *scaling* of the demand system. Brand advertising centers attention on attributes and images that can be associated with a specific brand. Thus, it is tied to brand loyalty and brand switching.

Three earlier studies (Goddard and Amuah; Piggott et al.; and Green) used translating to incorporate advertising expenditures in the Translog and AIDS models. Two analyses (Duffy; and Green, Carman, and McManus) considered scaling to incorporate advertising expenditures in the Rotterdam and AIDS models, respectively. In three other studies (Cox; Brown and Lee; and Brester and Schroeder), both translating and scaling effects of advertising within a Rotterdam model were examined.

In our analysis, we augment the Duffy model (scaling hypothesis) through the use of a polynomial inverse lag mechanism. Following Duffy, we describe a version of the Rotterdam model which includes advertising as well as real income and prices among the right-hand side variables. The first-order condition for utility maximization implies equality between the marginal utility for the ith good ($\partial u/\partial q_i$) and λp_i, where λ is the marginal utility of income and p_i is the price of the ith good. Duffy assumes the following relationship for the change in marginal utility due to a change in the volume of advertising (A_i) on a good i:

$$(1) \quad \frac{d(\partial u/\partial q_i)}{d \log(A_i)} = \gamma_i(\lambda p_i),$$

where $\gamma_i \geq 0$, and γ_i represents the elasticity of marginal utility with respect to advertising for the *i*th good.

Given (1), Duffy shows that the absolute price version of the Rotterdam model may be written as

$$(2)\quad \bar{W}_{it} d\log(q_{it}) = \alpha_i + \mu_i d\log(Q_t) + \sum_{j=1}^{n} \Pi_{ij}[d\log(p_{jt}) - \gamma_j d\log(A_{jt})] + u_{it},$$
$$i = 1, 2, \ldots, n; \qquad t = 1, 2, \ldots, T,$$

where $\bar{W}_{it} = (W_{it} + W_{it-1})/2$, and $d\log(Q_t) = \Sigma_i \bar{W}_{it} d\log(q_{it})$. To ensure that $\gamma_j \geq 0$ for all j, we let $\gamma_j = \tau_j^2$, where $-\infty < \tau_j < \infty$. In this model, $\bar{W}_{it}$ denotes a two-period moving average of the market share of spaghetti sauce i in time period t, q_{it} denotes the number of units sold of item i in time period t, and p_{jt} corresponds to the price of item j in time period t. The coefficient μ_i is the marginal budget share for the *i*th spaghetti sauce, and the coefficient Π_{ij} is the *ij*th element of the Slutsky matrix of the group of spaghetti sauces.

Empirical findings from previous studies support the hypothesis that advertising has carryover or lagged effects (e.g., Nerlove and Waugh; Waugh; Ward and Lambert; Ward and Dixon; Wohlgenant and Clary). However, theory provides relatively little guidance as to the structure and length of these dynamic processes. Conventionally, researchers, through the use of statistical criteria like the Akaike Information Criterion (AIC) or the Schwarz Loss Criterion (SLC), allow the data to choose the optimal number of lags to include in the specification of an advertising stock variable. The coefficients associated with the contemporaneous and lagged advertising expenditures also are commonly assumed to be a free-form lag or to follow some type of distribution, e.g., a geometric decay or a polynomial (or Almon) distributed lag. To illustrate, Piggott et al. consider the advertising process to follow a free-form lag of four quarters. Cox, as well as Brester and Schroeder, use a second-order exponential lag distribution of a particular length. Baye, Jansen, and Lee employ a geometric lag.

In our analysis, we deviate from the norm through the use of a polynomial inverse lag (PIL) specification (Mitchell and Speaker). With the PIL,

$$(3)\quad A_{kt} = \sum_{i=0}^{\infty} W_{ki} a_{k,t-i}, \qquad k = 1, 2, \ldots, n,$$

where

$$(4)\quad W_{ki} = \sum_{j=2}^{m} \frac{c_j}{(i+1)^j}, \qquad i = 0, \ldots, \infty.$$

The a_k notation represents advertising expenditures in levels, and c_j denotes parameters, where $j = 2, \ldots, m$.

The PIL has a flexible shape, allowing both humped and monotonically declining lag weight distributions. The lag is similar in spirit to the Almon lag; however, it is an infinite lag and thus requires neither specification of a fixed lag length nor imposition of endpoint restrictions. The use of the PIL only involves a search for the polynomial degree j $\{j = 2, \ldots, m\}$. Based on Monte Carlo work conducted by Mitchell and Speaker, the PIL outperforms several other popular distributed lag models.

Via algebraic manipulation, we may combine (3) and (4) as follows:

$$(5)\quad A_{kt} = \sum_{j=2}^{m} c_j \left[a_{kt} + \frac{a_{k,t-1}}{2^j} + \frac{a_{k,t-2}}{3^j} + \ldots + \frac{a_{k,t-l}}{(l+1)^j} + \ldots \frac{a_{k1}}{t^j} \right].$$

The subscript t corresponds to the observation of the series A_k. For $t = 1$, $A_{k1} = \Sigma_{j=2}^{m} c_j a_{k1}$; for $t = 2$, $A_{k2} = \Sigma_{j=2}^{m} c_j[a_{k2} + (a_{k1}/2^j)]$; and more generally for $t = l$ $\{l = 1, 2, \ldots, T\}$,

$$(6)\quad A_{kl} = \sum_{j=2}^{m} c_j \left[a_{kl} + \frac{a_{k,l-1}}{2^j} + \frac{a_{k,l-2}}{3^j} + \ldots + \ldots \frac{a_{k1}}{l^j} \right].$$

To use the PIL, one needs to generate the term in brackets in (6) for each of the $\{l = 1, 2,$

..., $T\}$ observations in the data set. Then, one needs to determine the optional choice of j (the degree of polynomial) using either the AIC or SLC.

In empirical application of the Rotterdam model, log differentials are approximated by log differences. In particular, $d\log(A_{kt}) \approx \log(A_{kt}/A_{kt-1})$. The expression for A_{kt} is given by (5).

The Rotterdam model necessitates the use of restrictions so that the estimates of demand parameters conform to theory. The restrictions for the Rotterdam model are as follows:

$$\text{(7)} \qquad \sum_i \mu_i = 1, \qquad \sum_i \Pi_{ij} = 0 \quad \text{(adding up)}$$

$$\sum_j \Pi_{ij} = 0 \quad \text{(homogeneity)},$$

and

$$\Pi_{ij} = \Pi_{ji} \quad \text{(symmetry)}.$$

Operationally, when estimating demand systems, one equation must be omitted to avoid singularity of the variance-covariance matrix of disturbance terms. In this application, the omitted equation corresponds to Newman's Own spaghetti sauce. Through the restrictions in (7), the demand parameters associated with the omitted equation are subsequently recovered.

The total expenditure elasticities, as well as the own- and cross-price and advertising elasticities, are defined as follows:

(8) Total Expenditure Elasticities:

$$\eta_i = \frac{\mu_i}{w_i},$$

Compensated Price Elasticities:

$$\epsilon_{ij}^* = \frac{\Pi_{ij}}{w_i},$$

Uncompensated Price Elasticities:

$$\epsilon_{ij} = \frac{\Pi_{ij}}{w_i} - w_j\eta_i = \frac{\Pi_{ij} - w_j\mu_i}{w_i},$$

and

Advertising Elasticities:

$$\delta_{ij} = \frac{-\Pi_{ij}\gamma_j}{w_i}.$$

Typically, the respective elasticities are calculated at the means of the data. That is, in (8), we replace w_i with $\bar{w}_{it}$. Weak separability of spaghetti sauces from all other commodity groups is assumed. As Pudney states, "Separability does not imply that between-group responses are necessarily small, only that they conform to a specific pattern" (p. 570). The bottom line is that, due to the assumption of weak separability, the relationships in the Rotterdam model are conditional demand equations.

Data

Our data set corresponds to weekly sales (in dollars) and movement (number of items sold) information collected by IRI over the period June 3, 1991 through May 31, 1992. This information comes from approximately 1,700 supermarkets located in 51 different market areas in the United States. The listing of the market areas and the associated number of supermarkets in the IRI sample are presented in table 1. Thus, the IRI data correspond to store-level information in particular market areas. The market areas, with some exceptions, correspond to major cities in the United States. For each supermarket in each market for each of the 52 weeks, IRI collects the sales and movement information for spaghetti sauces in 15- to 40-ounce containers. To account for differences in size, IRI standardizes the sales and movement information. In addition, IRI provides store-level information on: (*a*) the use of major or minor displays for spaghetti sauces, and (*b*) the use of features in newspaper fliers. The IRI data set corresponds to approximately 2.7 million records.

In this analysis, we aggregate the store-level/market-level information to develop national sales and movement figures for six spaghetti sauces: (*a*) Prego, (*b*) Ragu, (*c*) Classico, (*d*) Hunt's, (*e*) Newman's Own, and (*f*) private label brands. To develop price information by brand, we divide the national sales figures by the national movement figures. To take into account the number of supermarkets in the IRI sample, we divide the standardized movement information by the number of stores.

Table 1. Listing of IRI Market Areas and Number of Supermarkets in Each Sample

Market Area and Market Code Definition (51 markets)		
Pittsfield MA (6)	Denver CO (41)	New Orleans LA (40)
Charleston/Savannah SC (6)	Philadelphia PA (44)	Buffalo/Rochester NY (35)
Visalia CA (12)	Atlanta GA (34)	Charlotte NC (28)
Los Angeles CA (74)	Providence RI (23)	Hartford CT (33)
Chicago IL (56)	Cincinnati OH (30)	Jacksonville FL (29)
Memphis TN (30)	Indianapolis IN (29)	Louisville KY (24)
Houston TX (42)	Oklahoma City OK (26)	Richmond/Norfolk VA (30)
Pittsburgh PA (31)	Sacramento CA (28)	Columbus OH (30)
Seattle WA (40)	San Diego CA (30)	Omaha NE (23)
Detroit MI (39)	Portland OR (38)	Grand Rapids MI (21)
Cleveland OH (30)	Salt Lake City UT (25)	Little Rock AR (20)
St. Louis MO (39)	Phoenix AZ (43)	Wichita KS (24)
Dallas/Ft. Worth TX (50)	Miami FL (38)	Orlando FL (28)
Kansas City KS (25)	Nashville TN (27)	San Antonio TX (41)
Boston MA (48)	Raleigh/Durham NC (31)	Birmingham/Montgomery AL (45)
San Francisco CA (40)	Baltimore MD/Washington DC (46)	New York NY (81)
Tampa/St. Petersburg FL (38)	Milwaukee WI (27)	
Minneapolis/St. Paul MN (33)		

Note: Numbers in parentheses indicate the number of supermarkets in the IRI sample for the market area.

A total of 52 weekly observations thus are available in this analysis. In addition, data were collected on a weekly basis pertaining to the dollar outlays for television advertising contributed by manufacturers of Prego, Ragu, and Classico. Importantly, however, over this period, there were no expenditures for television advertising contributed by the manufacturers of Hunt's, Newman's Own, and private label spaghetti sauces. Also, IRI obtained weekly information on face value of coupons available to consumers for spaghetti sauces.

We augment the specification given in (2) by adding dummy variables to account for seasonality; we also add variables which correspond to the proportion of stores which use major or minor displays for spaghetti sauces and the proportion of stores which feature spaghetti sauces in newspaper fliers, and we take into account the weekly face value of coupons available to consumers for spaghetti sauces. Finally, to take into account possible habit/inventory effects, we add a lag of the dependent variable to each equation in the demand system. In this way, we provide for dynamics in our model specification.

The use of IRI data in market analyses is not unique to this study. Iskow, Kolodinsky, and Russo used movement data from IRI to analyze the demand for maple syrup. They estimated price and promotion elasticities for five leading brands. Cotterill, using IRI data, estimated demand elasticities for carbonated soft drinks, including Coke, Pepsi, and Dr. Pepper.

Descriptive statistics of the variables in the Rotterdam model are presented in table 2. Ragu and Prego capture 42% and 28%, respectively, of the national market for spaghetti sauces. Classico and Hunt's each account for roughly 10% of the national market. Private label brands comprise about 6% and Newman's Own about 4% of the national market. Given that Newman's Own constitutes the least of the market shares, this equation was omitted to avoid the singularity of the variance-covariance matrix in the demand system. In this analysis, the q_{it} variables correspond to the number of items of spaghetti sauce i sold per store in week t. Ragu, Prego, and Hunt's are the top spaghetti sauces in terms of item movement per store. Classico and Newman's Own sauces are the most expensive brands, while private label brands and Hunt's sauces are the least expensive.

A graphical representation of television ad-

Table 2. Descriptive Statistics of the Variables in the Rotterdam Model

Variable/Brand Name	Mean	Std. Dev.	Minimum	Maximum
Market Shares (w_{it}):				
Prego	0.2792	0.0223	0.2384	0.3307
Ragu	0.4177	0.0383	0.3579	0.4956
Classico	0.0975	0.0183	0.0720	0.1489
Hunt's	0.1007	0.0082	0.0847	0.1213
Newman's Own	0.0435	0.0036	0.0354	0.0526
Private Labels	0.0633	0.0063	0.0500	0.0802
Number of Items Sold per Store (q_{it}):				
Prego	134.55	17.81	104.45	177.53
Ragu	216.50	44.03	131.36	313.81
Classico	36.11	6.16	26.67	53.79
Hunt's	85.03	15.03	60.74	131.62
Newman's Own	17.70	1.87	13.91	22.29
Private Labels	42.49	8.03	30.06	65.10
Prices per Unit (p_{jt}) ($/unit):				
Prego	1.84	0.05	1.65	1.93
Ragu	1.73	0.07	1.57	1.86
Classico	2.38	0.07	2.22	2.51
Hunt's	1.06	0.03	0.94	1.11
Newman's Own	2.17	0.05	2.05	2.32
Private Labels	1.29	0.06	1.13	1.38
Television Advertising (A_j) ($):[a]				
Prego	47,121	62,721	0.00	234,880
Ragu	18,599	45,429	0.00	216,580
Classico	45,722	111,580	0.00	445,790
Display:[b]				
Prego	0.0653	0.0218	0.0259	0.1190
Ragu	0.1021	0.0256	0.0615	0.1835
Classico	0.0221	0.0114	0.0075	0.0491
Hunt's	0.0502	0.0129	0.0274	0.0752
Newman's Own	0.0076	0.0041	0.0009	0.0177
Private Labels	0.0941	0.0312	0.0445	0.1728
Featuring:[c]				
Prego	0.0886	0.0320	0.0268	0.1551
Ragu	0.1204	0.0524	0.0138	0.2782
Classico	0.0437	0.0305	0.0000	0.1494
Hunt's	0.0794	0.0400	0.0637	0.1926
Newman's Own	0.0140	0.0130	0.0000	0.0605
Private Labels	0.0670	0.0308	0.0537	0.1228
Face Value of Coupons ($):				
Prego	0.25	0.12	0.00	0.39
Ragu	0.21	0.08	0.00	0.29
Classico	0.15	0.20	0.00	0.46
Hunt's	0.11	0.02	0.00	0.06
Newman's Own	0.00	0.00	0.00	0.00
Private Labels	0.00	0.00	0.00	0.00

[a] There were no television expenditures for Hunt's, Newman's Own, and private label brands.
[b] Proportion of stores that have a minor or major display for promotion.
[c] Proportion of stores that feature in newspaper fliers for promotion.

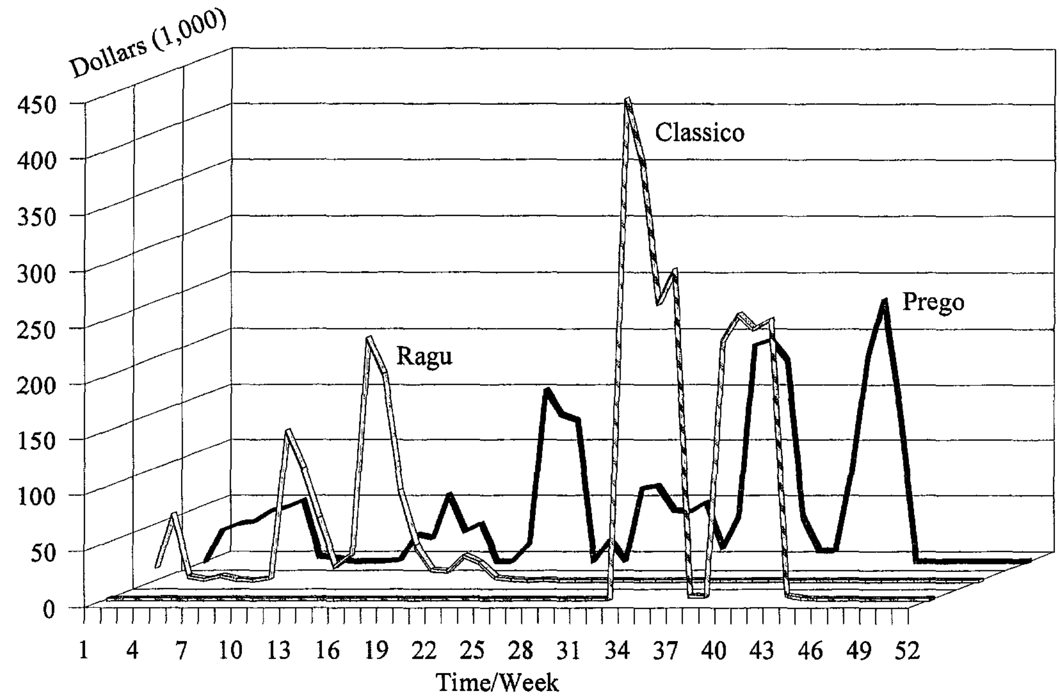

Figure 1. TV advertising expenditures for Prego, Ragu, and Classico spaghetti sauces (June 3, 1991 through May 31, 1992)

vertising expenditures is illustrated in figure 1. On average, manufacturers of Prego and Classico spent close to \$50,000 per week over the period June 3, 1991 through May 31, 1992. In contrast, the manufacturer of Ragu spent roughly \$20,000 per week over this time period. Moreover, for Prego, Ragu, and Classico brands, there were some weeks for which there were no advertising expenditures. In fact, for Classico, there were only eight weeks of non-zero dollar expenditures for television advertising. Under these circumstances, we arbitrarily assigned a value of \$1 in order to consider log transformations. There were no television advertising expenditures for Hunt's, Newman's Own, and private label brands at all over the sample period.

About 10% of the stores in the IRI sample had displays for Ragu and private label brands. Roughly 5–6% had displays for Hunt's and Prego. About 12% of the supermarkets made use of featuring for Ragu; 6–8% featured private label, Hunt's, and Prego brands in newspaper fliers. On average, the face value of coupons for Prego, Ragu, Classico, and Hunt's brands were 25¢, 21¢, 15¢, and 11¢, respectively. No coupons were available for Newman's Own and private label brands over the June 1991 through May 1992 time period.

Estimation Issues

The set of conditional demand equations is a nonlinear system of seemingly unrelated regressions. In the Rotterdam model, we also allow for first-order autocorrelation of the disturbance terms [an AR(1) process] by assuming

$$(9) \qquad u_{it} = \rho u_{it-1} + v_{it},$$

where the v's are independently and normally distributed. Conventionally, in demand systems (as shown by Berndt and Savin), the autocorrelation coefficient is the same across equations to ensure adding up. Piggot et al. relax the assumption of a common correlation coefficient in the estimation of the AIDS model. We, however, adopt the conventional approach to handling autocorrelation in our analysis. In addition, we assume that there is contemporaneous correlation among disturbance terms in different equations and that the disturbance terms follow a multivariate normal distribution.

Using the software package SHAZAM (version 7.0), estimates of parameters and standard errors are obtained via the method of maximum likelihood. Due to the adding-up conditions in the Rotterdam model, the covariance matrix of disturbance terms is singular; the equation for Newman's Own spaghetti sauce is deleted to circumvent this singularity. The nonlinear seemingly unrelated regression estimators are invariant with respect to the equation deleted since they are maximum likelihood estimators (Judge et al.). The nonlinear procedure assures the large-sample properties of consistency and asymptotic normality of the estimated coefficients so that conventional tests of significance are applicable.

Empirical Results

On the basis of the AIC and SLC, the degree of polynomial chosen in the PIL is 2. From (6), when $j = 2$ (the degree of the polynomial), and using the approximation from the Rotterdam specification that $d\log(A_{kt}) \approx \log(A_{kt}/A_{kt-1})$, estimating the coefficient c_2 is not possible.

Parameter estimates and standard errors of the coefficients in the Rotterdam model are presented in table 3. Also, table 3 includes estimates of the marginal budget shares and advertising coefficients. To judge statistical significance, we use a significance level of 0.05.

Serial correlation is evident in this system of conditional demand functions. The estimate of ρ ($-.9617$) is statistically different from zero. Goodness-of-fit statistics are within the range of .7747 to .9282. All own-price Slutsky terms (Π_{ii}s) are negative and statistically significant; with one exception, all cross-price Slutsky terms (Π_{ij}s) are positive. Given the positive cross-price terms, the respective spaghetti sauces indeed are substitutes. The latent roots of the conditional Slutsky matrix are 0, $-.17$, $-.19$, $-.28$, $-.50$, and $-.99$, confirming that this matrix is negative semidefinite with rank 5, as required by consumer theory.

Featuring in newspaper fliers, ceteris paribus, leads to increases in the number of items sold of Ragu, Classico, and private label brands, but to decreases in the number of items sold of Prego and Hunt's brands. The use of displays in stores is successful in the promotion of Ragu and Classico spaghetti sauces, but not for private label brands. The use of displays is not statistically important in effecting the movement of Prego and Hunt's spaghetti sauces. The use of coupons increases the demand for Classico and Hunt's brands, but decreases the demand for Ragu and Prego brands. Seasonality of purchases is evident only for the Classico brand and private label brands. The coefficients associated with the lagged dependent variables in the system are all statistically significant. Positive coefficients are indicative of habit effects, while negative coefficients are indicative of inventory effects. Habit effects, possibly attributable to brand loyalty, are at work for the Prego and Hunt's brands. Inventory effects are at work for the Ragu, Classico, and private label brands. Finally, the positive and significant coefficients of the intercept terms for the Hunt's brand and the private label brands indicate the presence of an upward trend in purchases over the June 1991 through May 1992 time period. The remaining coefficients associated with the intercept terms for other brands are not significantly different from zero.

Further, all marginal budget shares are positive and statistically significant. The marginal budget shares follow closely the market shares. The estimates of the advertising coefficients (τ_is) are positive for the Ragu and Classico brands. However, the estimate of τ_i for Prego, while significantly different from zero, is negative. The estimates of γ_i are the squares of the estimates of τ_i. The γ_is represent the estimates of the advertising coefficients for Prego, Ragu, and Classico brands. The estimates of the γ_is range from .00002 to .0074. Using the likelihood ratio test, we reject the hypothesis that the advertising coefficients are jointly equal ($\chi^2_2 = 99.58$), and we reject the hypothesis that they are jointly equal to zero

Table 3. Parameter Estimates and Standard Errors of the Coefficients in the Rotterdam Model

	Prego	Ragu	Classico	Hunt's	Newman's Own[a]	Private Labels
Slutsky Coefficients (Π_{ij}s):						
Prego	−0.6338*	0.3431*	0.0419*	0.1375*	0.0552*	0.0558*
	(−19.07)[b]	(11.98)	(2.52)	(8.81)	(8.76)	(7.92)
Ragu		−0.6663*	0.1195*	0.1046*	0.0516*	0.0473*
		(−13.13)	(6.90)	(5.03)	(8.94)	(3.80)
Classico			−0.2518*	0.0194	0.0267*	0.0442*
			(−15.53)	(1.42)	(4.75)	(5.14)
Hunt's				−0.2651*	−0.0008	0.0042
				(−14.28)	(−0.17)	(0.51)
Newman's Own					−0.1500*	0.0172*
					(−28.18)	(6.02)
Private Labels						−0.1689*
						(−23.43)
Featuring	−0.0664*	0.0093*	0.0405*	−0.0346*		0.0395*
	(−7.04)[b]	(1.71)	(5.84)	(−3.45)		(12.91)
Display	−0.0241	0.0536*	0.1104*	−0.0092		−0.0742*
	(−1.23)	(5.42)	(3.80)	(−0.43)		(−7.91)
Face Value of Coupons	−0.0016	−0.0228*	0.0301*	0.0240		
	(−0.56)	(−8.14)	(25.85)	(1.29)		
Seasonality (χ^2 statistic)[c]	16.21	12.69	1,044.67*	15.36		30.54*
	(0.1332)	(0.3138)	(0.0000)	(0.1663)		(0.0013)
Lag of Dep. Variable	0.0603*	−0.0073*	−0.1078*	0.0336*		−0.0120*
	(10.32)	(−1.97)	(−9.53)	(4.56)		(−2.60)
Intercept	0.0049	−0.0074	−0.0012	0.0049*		−0.0040*
	(1.12)	(−1.27)	(−1.29)	(2.52)		(−2.75)
μ_i	0.2799*	0.4660*	0.0541*	0.1215*	0.0291*	0.0491*
	(15.56)	(18.42)	(10.09)	(14.13)	(12.58)	(9.28)
τ_i	−0.0862*	0.0701*	0.0047	—	—	—
	(−5.89)	(20.08)	(0.50)			
γ_i (square of τ_i)	0.0074	0.0051	0.00002	—	—	—
R^2	0.8522	0.9282	0.7747	0.8926		0.9196
ρ [AR(1) process][d]	−0.9617*					
	(−41.11)					

* Denotes statistical significance at the 0.05 level.
[a] Omitted equation of the demand system.
[b] Numbers in parentheses are t-statistics.
[c] Numbers in parentheses are p-values.
[d] Common ρ form in the demand system.

(χ^2_3 = 475.14). This latter result suggests that the augmented Rotterdam model (i.e., with the inclusion of advertising expenditures) is statistically superior to the traditional Rotterdam model.

Estimates of the uncompensated price and total expenditure elasticities are presented in table 4. The respective own-price elasticities are elastic, ranging from −2.06 (Ragu) to −3.47 (Newman's Own). Given the disaggre-

Table 4. Estimates of Uncompensated Price and Total Expenditure Elasticities at Sample Means

Brand Name	Prego	Ragu	Classico	Hunt's	Newman's Own	Private Labels	Expenditure Elasticities
Prego	−2.5502	0.8103	0.0523	0.3918	0.1542	0.1386	1.0029
	(−2.2702)	(1.2292)	(0.1501)	(0.4928)	(0.1978)	(0.2001)	
Ragu	0.5100	−2.0610	0.1773	0.1381	0.0750	0.0448	1.1156
	(0.8215)	(−1.5950)	(0.2862)	(0.2504)	(0.1235)	(0.1132)	
Classico	0.2747	0.9938	−2.6361	0.1432	0.2496	0.4194	0.5551
	(0.4297)	(1.2257)	(−2.5820)	(0.1991)	(0.2737)	(0.4534)	
Hunt's	1.0293	0.5349	0.0752	−2.7541	−0.0605	−0.0316	1.2068
	(1.3663)	(1.0391)	(0.1929)	(−2.6326)	(−0.0080)	(0.0423)	
Newman's Own	1.0829	0.9066	0.5487	−0.0861	−3.4785	0.3562	0.6700
	(1.2700)	(1.1865)	(0.6141)	(−0.0187)	(−3.4493)	(0.3973)	
Private Labels	0.6874	0.4368	0.6430	−0.0111	0.2469	−2.8038	0.8006
	(0.9110)	(0.7713)	(0.7212)	(0.0695)	(0.2817)	(−2.7547)	

Note: Numbers in parentheses are estimates of compensated price elasticities at sample means.

gate nature of the spaghetti sauce products as well as the weekly data information, this result is not surprising. Total expenditure elasticities range from .55 (Classico) to 1.20 (Hunt's).

Estimates of the compensated price elasticities also are given in table 4. Of particular interest are the sign and magnitude of the cross-price terms. With two exceptions, the compensated cross-price elasticities are positive, indicating that the spaghetti sauce brands are substitutes for each other.

Estimates of the own- and cross-advertising elasticities are presented in table 5. Conforming to theoretical expectations, own-advertising effects are positive, while cross-advertising effects are negative. A 1% increase in own-advertising expenditures gives rise to a .017% increase in the number of Prego items sold per store, and a .008% increase in the number of Ragu items sold per store. A 1% increase in advertising expenditures for Prego gives rise to a .006%, .003%, .010%, .009%, and .007% decrease in the respective number of competing spaghetti sauces sold per store. A similar result is evident for the case of Ragu. The advertising cross-elasticity effects are smaller than the own-advertising elasticity effects. The own- and cross-advertising effects for Classico are almost inconsequential.

Concluding Comments

Our findings support those of Duffy, who reported: "The advertising-augmented Rotterdam model constitutes a useful and appropriate specification for estimating the influence of

Table 5. Estimates of Advertising Elasticities at Sample Means

Brand Name	Prego	Ragu	Classico
Prego	0.0168	−0.0060	−0.000003
Ragu	−0.0061	0.0078	−0.000006
Classico	−0.0031	−0.0060	0.000058
Hunt's	−0.0101	−0.0051	−0.000004
Newman's Own	−0.0094	−0.0058	−0.000014
Private Labels	−0.0067	−0.0037	−0.000016

advertising on the inter-product distribution of demand" (pp. 1065–66). Also, the PIL specification appears to perform well.

With few exceptions, all compensated cross-price elasticities are positive, indicative that the respective spaghetti sauces are substitutes in the Hicksian sense. Advertising efforts by industry leaders produce positive own-advertising elasticities and negative cross-advertising elasticities. Then, for manufacturers of Classico, Hunt's, Newman's Own, and private label brands, it is not advisable to ignore advertising efforts of Prego and Ragu. Likewise for manufacturers of Prego, it is not advisable to ignore the advertising efforts of Ragu and vice versa. Commonly, however, cross-advertising effects are omitted from single-equation specifications. On this basis, then, the systems approach may be more useful than the single-equation approach.

The use of featuring in newspaper fliers is effective in promotion of Ragu, Classico, and private label brands, but not so for Prego and Hunt's brands. The use of displays in stores is successful in the promotion of Ragu and Classico spaghetti sauces. Use of coupons works well to stimulate purchases of Classico and Hunt's brands, but not Prego and Ragu brands.

Further work in regard to the different ways to incorporate current and lagged values of advertising in demand systems seems appropriate. In this analysis, we used a PIL of advertising expenditures to capture current and lagged effects. Alternatively, a free-form lag or perhaps another distributional assumption might be employed. To check on the robustness of our results, alternative functional forms might be used, such as the AIDS model (similar to the work by Green, Carman, and McManus). Finally, one might consider the translating hypothesis in lieu of the scaling hypothesis to investigate the effects of advertising. Additional research efforts with micro-level data, such as IRI Infoscan data, are likely to lead to a better understanding of the impacts of branded advertising.

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