Economic Evaluation of Commodity Promotion Programs in the Current Legal and Political Environment

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Branded and Generic Promotion in a Complex Carbohydrate Demand System: A Structural Latent Variable Approach to Promotion Evaluation

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Introduction

The demand for potatoes and potato products changes over time for many reasons. While traditional demand systems have proven capable of estimating changes due to variation in relative prices and expenditure levels, the effects of changing tastes and information are less amenable to system estimation. Many studies include a variety of socioeconomic factors in order to proxy changing tastes--greater participation by women in the workforce, wider participation in leisure activities, or longer workdays are only a few of many trends that influence consumers' demand for convenience attributes of potatoes and potato products (Jones and Ward; McCracken; Gao and Guenthner; Guenthner, Levi and Lin; Capps and Love, Cox, et al, Capps, et al.). Similarly, consumer preferences may change with the acquisition of more information about characteristics of the product.

This information can come from a variety of sources. Brown and Schrader developed an index of cholesterol awareness (constructed from published media articles) to estimate the effect of health concerns on the demand for eggs. However, firms and trade associations provide the bulk of consumer information through advertising and promotion. Nelson argued that all promotion is informative to a certain extent, while Kotowitz and Mathewson refined this idea by arguing that providing consumers with better information about product attributes is the primary way in which promotion increases demand. Stigler and Becker ascribed a similar role to promotion, although through a different mechanism. As an input to a household production model, Stigler and Becker argued that the informative content of promotion increases demand through improving the household productivity. Rejecting the promotion-as-information idea, Dixit and Norman felt that promotion is inherently manipulative and so shifts tastes directly. While providing information about a product or product class should expand the demand for all related products, Dixit and Norman's approach suggested that advertising has only an allocative role and should not expand overall demand. Because promotion exists in many different forms, reality likely lies somewhere between these two positions, but differentiating between the two empirically is a difficult task.

Of course, the type of effect that a given promotion program has is likely to be a product of its objective. A particular method of promotion that is intended to be primarily informative will influence demand through the mechanisms described by Nelson, and Kotowitz and Mathewson, among others. However, promotions designed to "persuade or reinforce" consumers' purchase decisions are likely to operate directly upon tastes (Chang). These two types of messages loosely define the difference between generic and branded promotion. Whereas generic advertising tends to rely on providing consumer information and increasing product awareness, branded advertising is more persuasive and competitive in focus. Because informative advertising contributes to the consumers' stock of knowledge regarding a particular product, the effects of generic promotion are likely to linger beyond the dissemination of the message, while brand advertising will be forgotten with the next promotion by a rival. This notion suggests a simpler method of isolating their effects in empirical models of demand.

Whether a short or long-term influence on demand, empirical analyses of the effect of promotion treat promotion expenditure amounts as either translating or scaling variables (Green, Goddard and Cozzarin, Cox) based upon the approach of Pollak and Wales. The former approach assumes that advertising shifts each share equation within a demand system much as a change in expenditure does. However, if information is indeed the relevant determinant of demand, then promotion should be included in empirical models in a way that reflects its contribution to the stock of knowledge, which is unobservable, and not as a direct shift variable. Therefore, promotion amounts can, at best, only be defined as proxy variables for a latent information variable. As it is unobservable, the effect of information can only be observed indirectly through the behavior that it induces among consumers.

Because information is more appropriately viewed as a stock variable rather than a flow, the acquisition and use of information is akin to an investment decision. Ideally, information improves the level of utility from consumption both now and in the future, but the effect tends to decay over time as the information becomes less relevant. Researchers employ a variety of methods to estimate the dynamic effects of promotion-as-information (Lee and Brown; Liu and Forker; Kinnucan and Forker, Chang and Kinnucan; Cox). Recognizing that learning takes time, many studies incorporate lagged advertising expenditure amounts into a demand system. Others do not fix the lag structure, but rather let the data decide what form provides the best fit (Cox). Typically, none of these studies consider contributors other than promotion to the stock of knowledge.

Often, problems with latent variables are treated as errors-in-variables models and, as such, are estimated using instrumental variables methods and a small set of proxy variables. However, this approach can result in obtaining a different set of parameters on the latent variable, depending upon which proxies are used, and which instruments. To address the problem of nonuniqueness, this paper develops and estimates a structural model for the latent information variable. In a static context, this approach is called the multiple-indicator and multiple-cause model (MIMIC) that has origins in Zellner, Joreskog and Goldberger, and Goldberger (1972a,b; 1977), whereas if the latent variable is autoregressive, the model becomes a dynamic MIMIC, or DYMIMIC (Engle and Watson, 1981; Watson and Engle, 1983; Gao). The DYMIMIC model estimates the contribution of promotion and other socioeconomic variables to the unobservable stock of consumer knowledge and, in turn, estimates the effect of the latent information variable on the demand for fresh and frozen potatoes. Including both branded and generic promotion allows the model to differentiate between the effect of the two types of promotion. If generic promotion is indeed informative, and branded is rivalrous, then generic promotion will contribute to the latent variable value and the branded promotion will not. Indeed, this method can be interpreted as a test for the generic content of any promotional campaign--to the extent that it contributes to the latent stock of knowledge, the message influences the demand for all products within the relevant group and does not merely reallocate expenditure among close substitutes. In fact, including exogenous variables other than promotion allows for an alternative interpretation of the state variable in a more traditional way: as a measure of similarly unobservable consumer tastes.

The primary objective of this paper is to determine the effect of branded and generic promotion on the demand for fresh and frozen potato products within a dynamic, latent variable complex carbohydrate demand system. A complementary objective is to determine the roles of changing consumer tastes and product information on the demand for these products. The unique contribution of this paper lies in combining these two objectives in a single, structural model of demand, thereby explicitly estimating the impact of promotion on tastes, information, and, ultimately, demand.

The first section of the paper provides a general description of the specification of the dynamic, structural latent variable model. The second section discusses the incorporation of promotion into this model and offers a specific functional form to be used in its empirical application. The fourth section provides more detail on the definition of specific variables and the methods used in estimating the DYMIMIC model. The results of applying this procedure to estimate the effects of branded and generic potato promotion are discussed in the following section, while the sixth section concludes the paper, offering suggestions for future research and extending the results to the promotion of other products.

Econometric Model of Latent Variable Estimation

This section provides a general description of the DYMIMIC model and shows how promotion can be incorporated to explain changes in the structure of demand. In its most general form, this model allows promotion to determine the dynamic evolution of a single state variable with two possible interpretations--the state of consumer tastes or the state of product knowledge. Although this approach belongs to a more general class of state-space models widely used in engineering and physical sciences, applying the models to problems in agricultural economics is becoming more widespread (Chavas; Tegnes).

A state-space model consists of a series of measurement equations that describe the relationship between observable regressors, unobservable (or latent variables), and dependent variables. In the structural model, several factors are thought to determine unobservable taste and information effects, and as such, are termed cause variables. Similarly, other variables are of interest because they provide the most direct, observable evidence of changes in the latent variable and are therefore called indicator variables. There is one measurement equation for each of the indicator variables, relating values of the indicators to the latent variable and a disturbance term. To model the process governing the latent variable, this approach also includes a transition equation that allows the latent variable to be a function of its own past value, exogenous factors (causes), and a vector of disturbances. In general notation (Watson and Engle) the measurement equations are given by:

(1) $$y_t = \alpha_t x_t + \beta_t Z_t + e_t,$$

and the transition equations by:

(2) $$x_t = \phi_t x_{t-1} + \gamma_t F_t + G_t v_t,$$

where:

(3) $$\begin{pmatrix} v_t \\ e_t \end{pmatrix} = N\left(0, \begin{bmatrix} Q_t & 0 \\ 0 & R_t \end{bmatrix}\right).$$

and y is a vector of observable "measurements," x is a vector of unobservable state variables, Z and F are exogenous determinants of y and x, respectively, and e and v are random disturbances with covariance matrices given by R and Q. While x is potentially multi-valued, estimation in this case is considerably more complex so the case of only one state variable will be considered (Aigner, et al.).

Because the DYMIMIC is the most general of this class of models, it subsumes several other state-space specifications (Watson and Engle, 1983). For example, defining x_t as a vector of regression parameters, and α as a set of exogenous variables produces the time-varying coefficients model described by Chow. When $\phi = \beta = \gamma = 0$, equations (1) and (2) describe a standard factor analysis model. However, allowing for a non-zero ϕ under these conditions defines a dynamic factor analysis framework. If β and γ are not zero, but $\phi = 0$, the equations define a MIMIC framework used by Robins and West, Engle and Watson (1981), Gao and Shonkwiler, and Brumm. Clearly, if the latent variables are thought to exhibit time-series properties, then the most general form of state-space model is to be used.

Advertising Dynamics and the DYMIMIC Model

Whether promotion affects tastes directly through a persuasion effect, or by reducing transactions costs through an information effect, its influence on demand is indirect through a latent measure of information and taste. As Chang and Kinnucan suggested, typical demand studies assume the states of taste and knowledge are constant. Relaxing this assumption leads to a characterization of the consumer optimization problem as (Deaton and Muellbauer):

$$(4) \qquad Max\ U = U(q, \Xi) \quad s.t. \quad p'q = m.$$

where q is an nX1 vector of consumption quantities, Ξ is a latent variable, p is an nX1 vector of goods prices, and m is total expenditure. Again in general notation, the solution to (4) yields demand equations:

$$(5) \qquad q_i = q_i(p, m, \Xi).$$

Estimating (5) requires the specification of a theoretically plausible demand system. For the purposes of this study, and many before it, the Almost Ideal Demand System (AIDS) of Deaton and Muellbauer has several advantages. Beyond the desirable properties they describe, the fact that it is derived from an expenditure function of Gorman polar form means that it is affine in utility and, therefore, aggregates consistently across consumers (Green). Moreover, because the AIDS model falls in the class of flexible functional forms, it allows testing of the theoretical restrictions of demand theory (Chang and Kinnucan). Finally, Blanciforti and Green cited advantages in using the AIDS model to characterize changes in income and price elasticity over time. Adapting the AIDS model to include the effects of taste and knowledge uses a version of the translation method of Pollak and Wales (1980) described by Rossi.

The translation approach involves making the autonomous amount of expenditure a function of some explanatory variable. While this is a plausible way to model the information effects of promotion, the persuasive effects on taste are more likely to influence the slope parameters. However, modeling the effect both ways causes insurmountable estimation problems, so this study employs the simpler translating method to capture both the information and taste effects. In deriving the basic AIDS model, the minimum expenditure function dual to (4) is:

$$\text{(6)} \qquad \ln e(p, U) = a(p) + b(p)\, U;$$

where e is the minimum level of expenditure required to achieve the optimum level of utility, and a(p), b(p) are increasing, concave functions of the prices. Giving a particular functional form to a(p) and b(p) leads to the AIDS specification:

$$\text{(7)} \qquad a(p) = \alpha_0 + \sum_i \alpha_i \ln p_i + (1/2) \sum_i \sum_j \gamma_{ij} \ln p_i p_j ,$$

and:

$$\text{(8)} \qquad b(p) = \beta_0 \prod_i \ln p_i^{\beta_j} .$$

Substituting (8) and (7) into (6) gives an expression for the AIDS expenditure function. Applying Shephard's lemma to the result gives:

$$\text{(9)} \qquad w_i = \alpha_i + \sum_j \gamma_{ij} \ln p_j + \beta_i \ln (m/P),$$

where P is the Stone's price index: $P = \sum_i w_i \ln p_i$. and w_i is the budget share of good I. In this expression α_i does not necessarily have to be constant. In fact, allowing the intercept to vary with the latent variable is the essence of the translating method.

With this approach, the latent variable shifts every share equation. Green (1985) showed that this method preserves all of the theoretical requirements of an empirical demand system. In general terms, translation essentially allows the shifting variables to alter the level of discretionary income:

$$\text{(10)} \qquad q_i = s_i + q_i^*(p,\, m^*),$$

where m^* is interpreted as "supernumerary" income, and s is the level of subsistence expenditure on the ith good. Incorporating the latent taste and information variables into the LA/AIDS specification consistent with (10) leads to share equations of the form:

$$(11) \qquad w_i = \tau_1 \Xi + \sum_j \gamma_{ij} \ln p_j + \beta_i \ln (m^*/P),$$

where Ξ is the latent taste-and-information variable.[1] Specific definitions of each of the cause, indicator, and latent variable are included in the following section.

Data and Methods

This study uses annual data from 1970-1991 on retail-weight consumption of fresh (w_1), and frozen (w_2) potatoes, rice (w_3), pasta (w_4), and bread (w_5).[2] Per capita potato, rice, pasta, and bread consumption is found in USDA's *Food Prices, Consumption, and Expenditure*. Retail price data are taken from the annual report of the Bureau of Labour Statistics' *Consumer Price Index: Monthly Summary*. Data on the amount of food consumed away from home are found in various issues of the *Food Marketing Review*, the authors of which provide data on the proportion consumed as fast food. The number of microwaves in use and the participation rate of women in the workforce are both from Department of Commerce sources. Generic promotion data are from the National Potato Promotion Board, while the branded data are from Leading National Advertisers.[3] Although potato utilization includes a significant amount of chipping potatoes, it is felt that potato chips belong more appropriately to the "snack food" group and are not seen as a viable substitute for other starchy staple foods.

In terms of the state-space model structure, indicators of taste and information are the per capita expenditure on fast food and a ratio of fat calories consumed to carbohydrate calories. The latter variable is constructed from

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[1] Substituting the cause equation into this expression gives a specification very similar to Blanciforti and Green's habit formation model.

[2] As in Gao, et al., the bread variable is expressed in terms of wheat flour equivalents. As such, this variable includes many different types of breads and other bakery products.

[3] The authors thank E. Jones for providing the branded promotion expenditure data.

aggregate food consumption series published in *Food Consumption, Prices, and Expenditure* from the USDA. The indicator equations consist of the LA/AIDS shares and a group of factor loading equations that simply regress each indicator variable on the latent variable. This second group serves to scale the indicator variables subject to a random error. The cause variables include the percentage of women in the workforce, the number of microwaves in use, and the amounts of both branded and generic potato product promotion. The cause, or transition, equation includes each of these variables in addition to the lagged latent variable value and the random error term. Although this specification would allow the estimation of differential effects of branded and generic promotion on tastes and information, too few observations limit the model to ultimately include only fast food expenditure as an indicator of consumer demands for convenience, and their stock of information with respect to potato products.

As is often the case in estimating demand systems, there is some question as to whether prices or quantities are appropriately treated as exogenous variables (Thurman, 1987). In the former case, the direct LAIDS approach provides consistent parameter estimates, while the latter suggests that an inverse AIDS (LIAIDS) model should be used (Moschini and Vissa, 1992; Eales and Unnevehr, 1993). Thurman, Wahl and Hayes (1990), and Eales and Unnevehr each test for price and quantity exogeneity using the general Hausman specification test method. As Wahl and Hayes described, the Hausman test relies upon the existence of an estimator that is consistent under both the null and alternative hypotheses, but is not asymptotically efficient under the null and one that is consistent and asymptotically efficient under the null. In the complex carbohydrate model, price and quantity endogeneity of fresh and frozen potato products, pasta, and bread are each in question. Rice, on the other hand, presents less of a problem as there are strong *a priori* arguments for price exogeneity.

To test for the endogeneity of potato prices alone, ITSUR estimates of the system with fresh and frozen potato prices maintained as exogenous are compared to 3SLS estimates. For the 3SLS estimation, the set of instrumental variables includes variables that are highly correlated with potato prices, and yet are exogenous with respect to the supply of potatoes. Under the null, ITSUR will be consistent and asymptotically efficient, whereas 3SLS will be inefficient. Rejection of the null hypothesis in the LAIDS model means that potato prices are endogenous. A similar procedure is conducted with the LIAIDS tests for the endogeneity of potato quantities. Finally, the same test determines whether pasta and bread prices and/or quantities are endogenous.

As Wahl and Hayes (1990) explained, supply instruments are selected such that they are predetermined with respect to the endogenous variables in the system, and yet remain highly correlated with the explanatory variables. For fresh potatoes and frozen potato products, a U.S. average producer price index developed by Mischen (1994) and the average U.S. potato yield reported in the USDA's *Potato Statistics* are used to represent the cost of potato production. Processing cost instruments include a 'food and kindred products' labor wage rate, a fuels and energy price index, and the 90-day T-bill rate. These instruments are required to conduct the Hausman test in the complex carbohydrate data.

The first Hausman test considers the endogeneity of potato product prices in the LAIDS model. As Table 1 shows, the null hypothesis that fresh and frozen potato prices are exogenous cannot be rejected. Similarly for pasta and bread prices--in neither case can price exogeneity be rejected. However, applying the Hausman test to the LIAIDS model to test for the endogeneity of potato, pasta, and bread quantities shows that exogeneity of quantities also cannot be rejected. This means that either LAIDS or the LIAIDS models can appropriately be used for estimation.

Table 1. Hausman Tests of Price and Quantity Endogeneity

Variable[1]	Potato Products	Bread	Pasta
Quantity	5.1582	1.6744	1.3200
Price	7.4617	2.0734	5.6605

[a] Critical Chi-square at 5% level is 21.0300 for the potato products and 9.4900 for pasta and bread.

Given these results, the complex carbohydrate indicator equations are specified as an LAIDS model within the state-space framework.

One of the principal advantages in using the state-space specification of the DYMIMIC model is that parameter estimates are found using standard maximum likelihood methods within the recursive Kalman filter algorithm (Watson). In fact, this is a relatively common approach in estimating economic models with structural latent variables (Burmeister and Wall; Engle et al.; Slade; and Harvey). In agricultural economics, Chavas and Tegnes each used a Kalman filter to estimate time-varying regression parameters models, which are in turn used to test for structural changes in demand. While they defined regression parameters as state variables, the current example treats the stock of information and the state of tastes as a single latent state variable. Because interest lies in the evolution of information over time, and information is a latent variable, the estimation method must be able to provide estimates not only of the system parameters, but also of the latent variable itself. There are several methods for constructing the latent variable series from the structural model. Watson and Engle, Dempster et al., and Chen each described an iterative estimation and minimization (EM) algorithm. Watson and Engle in particular compared the EM method favorably to the method of scoring. This study adopts a somewhat simpler approach than either in applying the smoothing algorithm of Harvey (1989).

From the general state-space model description above, Engle and Watson (1981) defined two sets of unknowns that must be estimated with the Kalman filter--the vector of parameters, $\Phi = (\phi, \gamma, G, \alpha, \beta, Q, R)$, and the latent states, x_t. Estimating both the parameters and the unobservable variable requires a two-stage approach. In the first stage, initial values for the indicator equation parameters are found using standard regression methods. With these initial values, maximum likelihood estimates of the parameter vector Φ are found using the Kalman filter. Using the Kalman filter to re-estimate the latent variable series based on the maximum likelihood parameters produces estimates that, while linear and unbiased, are not best. Because Harvey (1989) showed that smoothing produces the minimum MSE estimates of the latent variable series, the second stage involves using this technique to recover the x_t values. Essentially, smoothing is a backwards recursive method that begins with the Kalman filter estimates of x_T, and then proceeds to estimate values of $x_{t|T}$ for each observation. Because smoothing produces estimates that are based not just on information up to t but from the whole sample, the resulting MSE must be at least as low as that obtained through filtering.

The log-likelihood function from the first stage estimation is quite simple. Define the innovations from estimating the indicator equations as:

$$\text{(12)} \qquad \eta_t = y_t - E[y_t | \Psi_t],$$

where Ψ_t contains all information up to time t, including the best estimates of y through (t-1) and any new information from the exogenous variables in time t (Engle and Watson, 1981). Defining the covariance matrix of η_t as H_t produces the log-likelihood function:

$$\text{(13)} \qquad \sum_t L_t(\Phi) = \sum_t - \frac{1}{2} \sum_t (\log|H_t| + \eta_t' H_t^{-1} \eta_t),$$

where Φ is a vector of parameters. Maximizing this log-likelihood function in GAUSS provides estimates of the DYMIMIC model parameters, while the smoothing algorithm provides estimates of the Ξ series.

Results

While the results support the general contention that a structural latent variable model is preferable to a standard proxy variable approach, few of the LA/AIDS price and expenditure parameters were significantly different from zero. Perhaps this was to be expected given the limited number of observations available and the larger number of parameters to be estimated. Given the objectives of this study, attention is focused on the role of the latent variable in each of the share equations, and the parameters of each of the cause variables in the transition equation. To test the superiority of the DYMIMIC model over a proxy variable approach, the null hypothesis is that the variance term in the fast food indicator equation (G) is equal to zero. If the data fail to reject the null hypothesis, then the DYMIMIC model has not been able to improve on the ability of a standard proxy variable model to explain the variation in complex carbohydrate demand remaining after all price and expenditure effects have been filtered out.

Table 2 presents the complex carbohydrate LA/AIDS estimates, including the latent variable parameters. Despite the fact that only 20 percent of the parameters were significantly different from zero, this includes four out of the five own-price coefficients. Of greater interest, however, were the latent variable coefficients. The latent information and taste variable had a statistically significant influence on rice demand at a 1 percent level, and on pasta demand at a 10 percent level of significance. Whereas this effect led to a reduction in rice demand, the opposite effect was true, albeit small, for pasta consumption. Because neither fresh nor frozen potato demand appeared to be influenced by the latent variable, this suggests that consumer demands for convenience dominate the effect of promotion in determining the value of the latent variable.

Table 2. DYMIMIC LA/AIDS Complex Carbohydrate Parameter Estimates: 1970-92

	Fresh Potatoes	Frozen	Rice	Pasta	Bread
P_{fresh}	0.7100 (0.5797)	0.0165 (0.0202)	-0.0152 (-0.0488)	-0.0451 (-0.2197)	-0.6754 (-0.6118)
P_{frozen}	0.3691 (0.4166)	1.9588** (3.9934)	-0.1594 (-0.7193)	-0.0398 (-0.2732)	-2.1240** (-2.7797)
P_{rice}	0.1821 (0.5859)	-0.3403* (-2.1565)	0.3091** (4.1213)	-0.0551 (-1.0889)	-0.0982 (-0.3825)
P_{pasta}	-0.1951 (-0.1438)	-0.4943 (-0.7194)	0.2145 (0.6363)	0.5166* (2.3083)	-0.0399 (-0.0242)
P_{bread}	-2.4851 (-0.8262)	0.5578 (0.3502)	0.5614 (0.7863)	0.0493 (0.1006)	1.2545** (3.9018)
M[a]	-0.1759 (-0.3551)	-0.2843 (-1.1290)	0.1603 (1.2062)	-0.0204 (-0.2353)	0.3092 (0.6252)
Ξ	0.1418 (0.4692)	0.0126 (0.0902)	-0.1887* (-2.4927)	0.0761 (1.4635)	-0.0304 (-0.1051)

[a] Variable definitions: M = total complex carbohydrate expenditure; Ξ = latent stock of information; P_i = retail price index of each complex carbohydrate. T-ratios are in parentheses, where a single asterisk indicates significance at 5% and a double asterisk indicates significance at 1%.

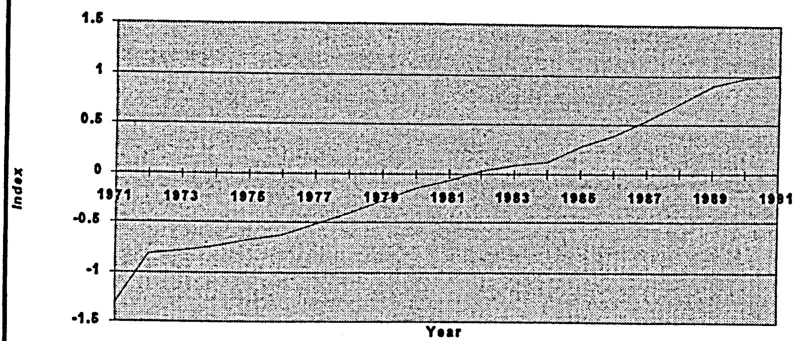
Estimates of the cause equation show this to be precisely the case. Whereas women's participation rate in the workforce and the number of microwaves in use were both highly significant, neither type of promotion was significant. Table 3 shows that both of the significant cause variables have a positive effect on the latent variable. Because the latent variable rose monotonically over the sample period as shown in Figure 1, this suggests that the change is largely determined by the demand for convenience and, to a lesser extent, branded promotion of frozen potato products. Based on the point estimates in this equation, generic promotion had a negative effect on the latent variable. Combining this result with the demand parameter estimates suggests that generic promotion, if it indeed has an effect, reduces the consumption of pasta but increases the demand for rice. This result also suggests that of the two alternative interpretations of the latent variable (as a stock of information or the state of tastes), the latter is more plausible.

Table 3. DYMIMIC Cause Parameter and Indicator Variance Estimates

Cause	Estimate	Std. Error	R Element	Estimate	Std. Error
Women	0.2764**	0.0814	R_F	0.1618**	0.0371
Microwave	0.0720**	0.0185	R_Z	0.0826**	0.0189
Generic Adv.	-0.0690	0.0890	R_R	0.0391**	0.0101
Branded Adv.	0.0715	0.0970	R_P	0.0265**	0.0065
Q	0.0000	0.0494	R_{FF}	0.1227**	0.0363
Ξ_{t-1}	0.0001	0.0070			

[a] A single asterisk indicates significance at a 5% level, and a double asterisk indicates significance at a 1% level. The diagonal elements of the R matrix reported here are standard deviations of the indicator equations. In the subscripts, F=Fresh, Z=Frozen, R=Rice, P=Pasta, FF=Fast Food.

Figure 1. Smoothing Estimates of Latent Variable Index (1971-1992)



Although promotion does not appear to help explain the change in structure of complex carbohydrate demand, this result helps in establishing a difference between the effect of branded and generic promotion. Recall the central hypothesis that only generic promotion is expected to contribute to the stock of information, and will therefore have a persistent effect on demand. Branded promotion, on the other hand, will only have a reallocative effect within the current period. Thus, differentiating between the two relies not only on their significance in the cause equation, but also the dynamics of the latent variable itself. Notice from Table 3 that the coefficient on the lagged latent variable is, in fact, insignificant. One interpretation of this result is that the lack of persistence in the latent variable indicates that generic promotion cannot be having its desired effect, and that branded promotion, if anything, is more successful in changing tastes.

One advantage of estimating a structural latent variable model such as this one is that it allows the decomposition of taste change by product. Because the DYMIMIC approach provides an estimate of the latent variable value for each observation, multiplying the latent variable by its coefficient in the respective share equation shows how changes in taste have influenced consumption of that product. Because the latent variable is significant in only the rice and pasta equations (at a 10 percent level), only these are used for demonstration of this point. Figure 2 provides a time-series plot of the effect of changing tastes on the demand for these two products. As the parameter interpretation suggests, the latent effect causes the share of rice to fall over time, while the share of pasta increases over the entire period.

Figure 2. Effect of Latent Variable on Rice and Pasta Consumption Share (1972-1992)

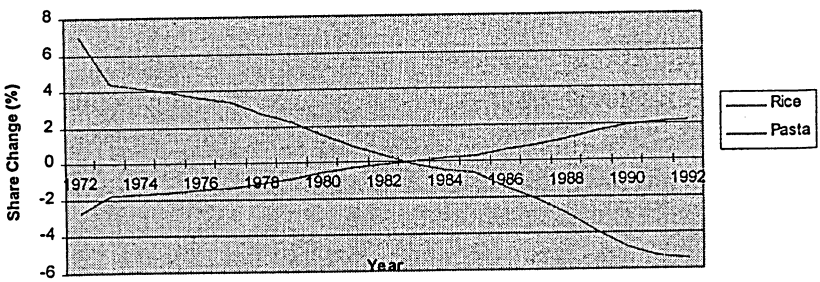


Table 3 also shows estimates of the covariance matrix, R, from the indicator equations in expression (3). As suggested above, the final diagonal element of this matrix--the standard error of the fast food indicator equation--is of particular interest. If this estimate is significantly different from zero, then the latent variable itself is a significant factor in explaining variation in complex carbohydrate demand. The fact that this parameter is highly significant suggests that the latent variable model represents an improvement over the standard proxy variable approach. In particular, the significance of this parameter indicates that the inclusion of an indicator variable with the DYMIMIC approach provides the identifying information that is absent in more typical errors in variables (EIV) models (Aigner, et al).

Although the structural demand parameters are of lesser importance in this paper, Table 4 reports the own- and cross-price elasticities of demand, as well as the expenditure and latent variable elasticities. While bread and pasta are shown to be price inelastic, rice appears to be highly elastic. The positive price elasticities for both fresh and frozen potatoes are likely products of the limited number of observations in the data set. As expected given these positive price elasticities, both fresh and frozen potatoes appear to be strongly inferior products. This does not bode well for future efforts to promote either product. On the other hand, bread and rice are luxuries, while pasta is a necessity. The latent variable elasticities confirm the parameter results above. While the elasticity of rice consumption with respect to the latent variable is strongly negative, the opposite is true for pasta. Furthermore, the point elasticity estimates for both fresh and frozen potato products with respect to the latent variable are strongly positive. The elasticity of bread with respect to tastes is also positive, although it is below 1.0. These results suggest that tastes are moving away only from rice, but towards the rest of the complex carbohydrate group.

Table 4. DYMIMIC LA/AIDS Complex Carbohydrate Elasticities: 1970-92

	Fresh Potatoes	Frozen	Rice	Pasta	Bread
P_{fresh}	5.4965	13.2090	9.2420	6.6971	0.6209
P_{frozen}	3.5056	0.3443	-1.1176	-0.6361	-1.0926
P_{rice}	1.6674	-2.3591	-5.5247	-0.5488	-3.3347
P_{pasta}	-1.6312	-3.3779	6.8556	-0.8098	-0.1652
P_{bread}	-2.1023	5.2789	15.3867	0.9296	-0.0934
M[a]	-0.5657	-8.5677	6.3948	0.6968	1.4757
Ξ	2.2622	1.4240	-5.3504	2.1309	0.9533

[a] Variable definitions: M = total complex carbohydrate expenditure; Ξ = latent stock of information; P_i = retail price index of each complex carbohydrate.

Conclusions and Implications

Generic and branded promotion are thought to differ in the persistence of their effects on demand. Whereas generic promotion contributes to consumer information, and thus should last for many periods, branded promotion's effect is likely to be more transitory. This paper develops a structural latent variable model of complex carbohydrate demand in order to test for this difference. The latent variable model defines an unobservable quantity measuring the stock of knowledge, or the state of tastes. Using a state-space model definition, the indicators of the latent variable include fast food expenditures and the complex carbohydrate budget shares from a LA/AIDS model. These are the measurement equations, while cause equations linking exogenous factors to the latent variable constitute the transition equations. This model is estimated using a Kalman filter algorithm. Including generic and branded promotion among the set of cause variables allows the model to test for the contribution of promotion to changing tastes for potatoes and potato substitutes.

The complex carbohydrate DYMIMIC model (including fresh potatoes, frozen potatoes, rice, pasta, and bread) is estimated with annual data from 1970-1992. The results show that the latent variable has a significant influence only on the demand for rice and pasta. In the former, tastes tend to reduce consumption, while taste changes tend to favor pasta. In the cause equation estimates, both of the taste-related cause variables have a significant effect on the latent variable, while neither generic nor branded promotion has any effect. This suggests that taste change dominates the latent information effect of generic promotion, and that nonpromotion trends similarly dominate branded promotion. The lack of significance of the lagged latent variable in this equation supports this finding in that transitory effects appear to be more important than those that depreciate slowly over time. Despite these somewhat negative results, the estimates do show that the DYMIMIC approach is the appropriate way to model structural changes in demand when such changes are unobservable and can come from many sources.

Future research in this area can extend along many lines. First, a deeper data set will allow the definition of more indicator variables, perhaps to more directly capture the influence of promotion on consumers' stock of knowledge. Second, Aigner, et al. suggest that the use of multiple latent variables will improve the performance of the model as whole. Clearly, treating information and tastes as separate state variables is step a in this direction. Third, the parameter estimates may be improved without obtaining more data through respecifying the demand system as unconditional.[4] This would reduce the bias that potentially exists in the current estimates due to the likely endogeneity of complex carbohydrate expenditures (Lafrance; Edgerton). A fourth area for improvement concerns the nature of USDA consumption data. Adjusting the published "per capita consumption" figures, which are in fact per capita utilization, for net exports and storage will more closely approximate the true amount consumed by U.S. households. Other variables may serve as better indicators of the value of leisure time in the household production model. Women's wage rates, overtime hours, and the amount of time spent in leisure activity are but a few of the alternatives deserving consideration.

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[4] This and the following suggestions were made by Dr. M. Wohlgenant at the NEC-63 meetings in Monterey, CA., Oct. 7-8, 1996.

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