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By

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ABSTRACT

"Commodity promotion" consists of many activities, each designed to contribute to a consumer's product knowledge or influence tastes. However, both knowledge and tastes are unobservable, or latent, variables influencing demand. This paper specifies a dynamic structural model of fresh fruit demand that treats promotion and other socioeconomic variables as "causal" variables influencing these latent variables. Estimating this state-space model using a Kalman filter approach provides estimates of both the system parameters and a latent variable series. The results show that these latent effects contribute positively to apple and other fruit consumption, while reducing banana consumption.

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Regional or state commodity promotion boards often hold market share in their particular

commodity as a primary goal. However, increasing imports, a wider variety of available

substitutes, or declining consumption of the commodity itself causes targeting the share of a

declining market to be somewhat misguided. Rather, commodity boards are increasingly

interested in strategies to increase demand for their product, preferring to compete for a share of a

growing market.   This is particularly true of the U.S. apple market. Whereas Washington apple

growers' share of U.S. fresh apple consumption has risen from 22.6% to 62.9% between 1951

and 1994, rising banana and other fresh fruit consumption (figure 1) has caused promoters of

Washington apples to question the viability of continuing a market-share strategy in the future.

Whereas their interest in the past has centered on the factors that determine Washington market

share, Washington growers must now turn to the determinants of apple-category share and an

explanation for the rise in banana consumption.

Many factors can explain such a change in product-demand. 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.[1] Many studies include a variety of socioeconomic factors in order to proxy trends in

consumer tastes -- principally towards more healthy diets and more convenience in meal

preparation (Senauer, Asp and Kinsey). 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. While consumers can actively search for products with traits they desire, firms and trade associations provide the bulk of consumer information through advertising and promotion. Nelson argues that all promotion is informative to a certain extent, while Kotowitz and Mathewson refine this idea in arguing that providing consumers with better information as to product attributes is the primary way in which promotion increases demand. Stigler and Becker ascribe a similar role to promotion, although through a different mechanism. As an input to a household production model, Stigler and Becker argue that the informative content of promotion increases demand through improving household productivity. Rejecting the notion that promotion merely provides information, Dixit and Norman argue that promotion is inherently manipulative and so shifts tastes directly. While providing information about a product or product class should expand the demand for both the promoted product and all close substitutes, or have a significant "generic" effect on the demand for the product-class, Dixit and Norman's approach suggests that promotion has only an allocative, or brand-specific, role. These conceptual arguments, however, consider promotion activities as homogeneous.

Whereas mass advertising is more likely to convey price or quality information, retail promotions (such as coupons, in-store displays, product giveaways) are intended to initiate purchase within the store. Because mass, or direct advertising contributes to consumers' stock of knowledge or long-term tastes regarding a particular type of product, its effects are likely to linger beyond the dissemination of the message, while efforts to create impulse purchases may last only for the duration of a single shopping trip. This suggests that a dynamic model may be able to test for the relative strength of an activity's generic, as opposed to its brand, effect. This paper

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develops a model designed to achieve this objective, where the dynamics arise through consumer

tastes or their stock of information, rather than the promotion itself.

Whether promotion is intended to affect the stock of information or consumer tastes, both

are unobservable, or latent, variables. The usual method of dealing with this latency, following

Pollak and Wales, consists of including promotion expenditure as either a translating or scaling

variable in a demand system as a proxy variable (see, for example, Goddard and Cozzarin, among

many others). However, this approach can result in a different set of parameter estimates

depending upon which proxies are used and, if an instrumental variable method is used, on the set

of instruments. To address the problem of non-uniqueness, this paper develops and estimates a

structural model for the latent information variable. As explained in more detail below, this

approach uses the covariance structure among a set of "indicator" variables and direct

relationships with a set of "cause" variables to identify the latent variable value. When several

indicators and cause variables are employed, this approach is called the multiple-indicator and

multiple-cause model (MIMIC) that has origins in Joreskog and Goldberger, and Goldberger

(1972a,b; 1977). Not only do promotion-evaluation studies typically rely on proxies for these

latent variables, but their methods of accounting for persistent effects of promotion are usually ad

hoc.[2] In a structural latent variable framework, if the latent variable is autoregressive, the model

becomes a dynamic MIMIC, or DYMIMIC (Engle and Watson; Watson and Engle; Engle, Lilien,

and Watson; Gao). As a result, the model is able to describe the evolution of the latent variable

itself, rather than a proxy.

A DYMIMIC model also provides estimates of the contribution of promotion and other

socio-economic variables to the unobservable states of consumer knowledge and tastes and, in

turn, the effect of these latent variables on the demand for fresh fruits. Further, by including both

consumer advertising and retail promotion as observable "causes" of the latent variables in a

demand system framework, this approach is able to differentiate between the effectiveness of each

method in expanding the demand for specific fruits. Moreover, factors other than promotion can

potentially influence latent demand variables. By including variables that capture consumer trends

towards healthy eating or convenience in meal preparation among the set of cause variables, this

approach is better able to provide estimates of the true effectiveness of promotion, independent of

other factors that may be influencing the demand for fresh fruit.

Therefore, the primary objective of this paper is to determine the effect of direct

advertising, retail promotion, and other factors on the apple-share of fresh fruit demand. The first

section of the paper provides a general description of the specification of the dynamic, structural

latent variable model. The second section explains how promotion is incorporated into this model

and offers a specific functional form to be used in the empirical application. More detail on the

definition of specific variables and the methods used in estimating the DYMIMIC model are

provided in the third section, while the following section describes and explains the estimation

results. Drawing on these results, a final section offers suggestions for future research and draws

implications for the promotion of other products.

Econometric Model of Unobservable Factors Influencing Fruit Demand

This section provides a general description of the DYMIMIC model and shows how promotion

can be incorporated to help 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

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two possible interpretations -- the state of consumer tastes or the state of product knowledge. Both are common in the commodity promotion literature. Although this approach belongs to a more general class of state-space models that are widely used in engineering and physical sciences, their application to problems in agricultural economics are becoming more widespread (Chavas; Tegene).

A state-space model consists of a set of measurement (or indicator) equations and a set of transition (or dynamic cause) equations. Measurement equations specify observable indicator variables as functions of the unobserved, or latent, variable and a series of predetermined variables, and a stochastic error term. Including this error term reflects that fact that the indicators are only imperfect measurements of the latent variable. The transition equations, on the other hand, describe the dynamic process of the latent variable. These equations, more often called cause equations in a static model, treat the current value of the latent variable as a function of its own past values, a vector of exogenous cause variables, and a stochastic disturbance term. Cause variables are selected based upon their hypothesized direct relationship to the unobservable variable. Another way of interpreting these two sets of variables is to think of cause variables as determining unobservable taste and information effects, while indicator variables provide the most direct, observable evidence of changes in the latent variable. There is one measurement equation for each of the indicator variables, relating values of the indicators to the latent variable, exogenous factors, and a disturbance term . In general notation (Watson and Engle) the measurement equations are given by:

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

In the empirical example of this paper, the transition equations provide a parametric

representation of the dynamics of the latent variable, as influenced by a set of cause variables, and

a stochastic error term:

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

where:

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

and y is a vector of observable "measurements", x is a vector of unobservable state variables, Z is

a vector of exogenous determinants of y, F is a vector of exogenous variables assumed to "cause"

x, e and v are random disturbances with covariance matrices given by R and Q. Because

identifying the latent variable value relies on using information contained on covariances between

the cause and indicator variables, this parameter is identified. 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.).

    There are, however, many cause variables used to explain this latent variable, and

indicators used to identify its value. Indicators should represent manifestations of the economic

factors that the latent variable is intended to represent. In this example, the first set of indicators

consists simply of fitted fresh-fruit demand shares derived from estimates of an Almost Ideal

Demand System (AIDS) (Gao and Shonkwiler). Also, the percentage of women in the workforce

serves as an indicator of consumer tastes towards more convenient and easy-to-prepare foods.

This variable may also represent a growing need for information on product characteristics -- the less time spent in meal preparation, the less time people have in learning about the nutritional and preparatory aspects of different foods. Cause variables, on the other hand, can be thought of as explanatory variables of the larger trend or trends that the latent variable is intended to represent. In the fruit-demand model, the set of cause variables consists of the percentage of food expenditure allocated to fast food, the ratio of fat calories to carbohydrate calories available in the U.S. food supply, and the dollar amount of expenditure by the WAC on direct advertising and retail promotion. The first cause variable, "fast food" is intended to capture consumers' tastes towards greater convenience in meal preparation, while the ratio of fat to carbohydrate calories represents their taste for either more, or less healthy diets, or perhaps improved information on the health consequences of their diet.[3] Direct advertising by the WAC is intended to represent efforts to provide broad nutritional, price, and availability information on Washington apples to consumers.[4] Retail promotion, on the other hand, provides a measure of the WAC's efforts to move apples into the retail channel through coupons, retail displays, promotion allowances, joint marketing efforts, or other "push" type strategies. Together, these cause and indicator variables form the DYMIMIC model structure.

Because the DYMIMIC is the most general of this class of structural latent variable models, it subsumes several other state-space specifications (Watson and Engle). For example, defining x_t as a vector of regression parameters, and α_t 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, but allowing for a non-zero ϕ under these conditions defines a dynamic factor analysis framework. If β and γ are non-zero, but $\phi = 0$, the

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equations define a MIMIC framework used by Robins and West, Engle and Watson, 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. The following section

describes the demand system used to provide the majority of indicator variables in the general

DYMIMIC model.

Advertising Dynamics and the DYMIMIC Model

Whether promotion affects tastes directly through a persuasion effect, or by reducing transactions

costs through an information effect, this paper assumes that its influence on demand is indirect

through a latent measure of information and taste. As Chang and Kinnucan suggest, demand

studies typically assume the states of taste and knowledge are constant. Relaxing this assumption

means that consumer utility can be written as a function of both quantity and the latent state

variable:

(3) $Max \ U \ = \ U(q, \Xi) \quad s.t. \quad p^{/}q \ = \ m.$

where q is an nX1 vector of consumption quantities, Ξ is the latent variable, p is an nX1 vector of

goods prices, and m is total expenditure. Solving (4) yields demand equations:

(4) $q_i \ = \ q_i(p, m, \Xi).$

Estimating (4) requires the specification of theoretically plausible demand system. For the

purposes of this study, and many before it, a linear approximate version of the AIDS (LAIDS) 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 LAIDS 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

cite advantages in using the LAIDS model to characterize changes in income and price elasticity

over time.[5]

Adapting the LAIDS model to include the effects of taste and knowledge uses a version of

the translation method of Pollak and Wales or 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. Including the latent variable with this method

results in a share system whose typical element is:

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

where Ξ is the latent taste-and-information variable and 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.[6] Green shows 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. The following

section provides specific definitions of each of the cause, indicator, and latent variables.

Data and Methods

This study uses annual data from 1951-1994 on retail-weight consumption of fresh apples (w_1),

bananas (w_2), fresh oranges (w_3), other fresh fruit (w_4), and other food (w_5). Per capita

consumption of these products is from USDA's *Fruit and Tree Nuts* from 1970-1994 while data

prior to 1970 are provided by USDA staff from archive. Retail price data are taken from the

annual report of the Bureau of Labor Statistics' *Consumer Price Index: Monthly Summary*. In

order to keep the model as parsimonious as possible, the "other fresh fruit" variable is constructed

as a composite of grape, peach, pear, and strawberry consumption. An average price for this

group is constructed using a Stone's price index, which uses expenditure shares as weights.

While each of these fruits is individually less than 10% of total fresh fruit expenditure, together

they represent an average 24.6% of fresh fruit spending over the sample period. This compares to

15.5% for apples, 48.2% for bananas, and 11.7% for oranges. By including "other food" in the

demand system as well, the resulting parameter estimates are interpreted as conditional on total

food expenditure. Further, this specification assumes that food spending is weakly separable from

all other consumer expenditure, a much weaker assumption than that used by other fruit demand

studies (Green, Carman, and McManus). The "other food" variable is constructed by subtracting

total fresh fruit expenditure from total food expenditure per capita reported in *Food

Consumption, Prices and Expenditure* from the USDA and dividing the result by a food

Consumer Price Index reported by the Bureau of Labor Statistics, after first adjusting the index

for the contribution of fresh fruit.

Data for the cause and indicator variables come from a variety of sources. The proportion

of food expenditure consumed away from home is from various issues of the *Food Marketing

Review*, the authors of which provide data on the proportion consumed as fast-food. Information

on the ratio of fat to carbohydrate calories is provided by researchers at the Center for Nutrition

Policy and Promotion in Washington, D.C. It is important to note that these data are in terms of

food energy available per capita per day available in the U.S. food supply, and not necessarily calories consumed. Differences between these two values may be due to waste, food that is given away, or placed in storage. Both direct apple advertising and retail promotion are taken from WAC records. Advertising consists of expenditure on television, radio, billboards, magazines and newspaper copy, but no breakdown of expenditures by media is available. Further, because no reliable cost measure nor expenditure share exists for these media, total expenditures are an imperfect measure of advertising intensity. Similarly, retail promotion expenditures cover a wide variety of activities from trade shows to cents-off coupons, so a reliable cost measure is also difficult to derive. Among the indicator variables, women's participation rate in the work force is from the Bureau of Labor Statistics, while the fitted fruit-shares are taken from the demand system described above. With these data, estimates of the latent variable model are obtained using an algorithm that is becoming common in estimating state-space models.

In fact, 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). Many recent studies employ this technique in analyzing a variety of economic problems with structural latent variables (Burmeister and Wall; Engle et al.; and Harvey). In agricultural economics, Chavas and Tegene each use a Kalman filter to estimate time-varying regression parameters models, which are, in turn, used to test for structural changes in demand. While they define regression parameters as state variables, the current example treats the stock of information and 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

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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 describe an iterative estimation and minimization (EM) algorithm. Watson and Engle in particular compare the EM method favorably to the method of scoring. This study adopts a somewhat simpler approach than either in applying Harvey's "smoothing" algorithm.

From the general state-space model description above, Engle and Watson define two sets of unknowns that must be estimated with the Kalman filter -- the vector of parameters, $\Phi = (\phi, \gamma, \alpha, \beta, Q, R)$, 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 reestimate the latent variable series based on the maximum likelihood parameters produces estimates that, while linear and unbiased, are not best. To find parameters that are indeed best, Harvey shows that smoothing produces the minimum MSE estimates of the latent variable series. Therefore, 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:

$$\eta_t = y_t - E[y_t|\Psi_t],$$

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). Defining the covariance matrix of η_t as H_t produces the log-likelihood function:

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

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

Given the greater complexity of a DYMIMIC as opposed to a conventional regression model, the first task is to determine whether or not the DYMIMIC approach represents an improvement over a more conventional, or even on a static MIMIC model. Once this is established, the discussion returns to the objectives of the paper, namely, evaluating the relative effects of direct advertising, retail promotion, and socio-economic trends on the demand for fresh fruit. Tests of these hypotheses examine 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.

There are three tests of the validity of the DYMIMIC model. First, to test the superiority of the DYMIMIC model over a proxy variable approach, the null hypothesis is that the variance term (G) in the transition, or cause equation (2) 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 fresh fruit demand remaining after all price and

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expenditure effects have been filtered out. Second, the null hypothesis in the transition equal is that the coefficient on the lagged latent variable value is equal to zero. Failure to reject this hypothesis supports a static MIMIC specification over the DYMIMIC one.   Third, if the coefficients of the latent variable in each of the indicator equations (also known as factor loadings) are equal to zero, then the model adds nothing to a demand model that includes only price and income effects. Table 1 presents the results pertaining to the transition equation and the disturbances from the measurement equations, while the fresh fruit LAIDS estimates, including the latent variable parameters are in table 2.

The results in table 1 show that the DYMIMIC specification is preferred to both a conventional regression model and a MIMIC approach. In this table, the *G* parameter is significantly different from zero, which suggests that the latent variable explains a significant proportion of the variability in fruit demand that is not already explained by the cause variables, which, in more conventional models, would be used as proxies. Further, the fact that the coefficient on the lagged-latent variable is significantly different from zero suggests a preference for the dynamic specification over the static model. Because this parameter is less than 1.0, the dynamic process of the taste and information variable is stationary, or, in more intuitive terms, shocks to the latent variable disappear over time so have little effect on demand more than a few periods in the future.

Table 2 provides the results necessary to determine whether tastes and information help explain the structure of fresh fruit demand. First note that the R^2 for four of the five equations is relatively high, indicating that this model provides a good fit to the data. Second, from these results, it is clear that the latent index is significant in some of the share equations. Specifically,

this index has a significant and positive effect on apple, other fruit, and other food consumption, while it has a negative effect on banana consumption. While the positive effect of tastes on apple consumption is perhaps surprising, the response of other fruit is not. Consumers now have a choice from a variety of fresh fruits available year-round through imports and controlled-atmosphere storage that were only available in-season during the 1950s and 1960s. Because consumers can now buy grapes year-round, due to imports from Chile and other Southern Hemisphere countries, total per capita consumption of grapes from all sources has risen dramatically as consumers buy grapes habitually as a part of every shopping trip, rather than just as a special treat in the summer (Alston et al.). Further, the introduction of new fruits such as the kiwifruit and seedless oranges and melons has created products that didn't exist at the start of the sample period. The negative banana-effect suggests that the observed trend towards banana consumption may be due more to price and income effects than to tastes for convenience, or a greater amount of consumer information regarding the health benefits of banana consumption. Indeed, the elasticities reported in table 3 show that this negative effect on banana consumption is not only statistically significant, but economically significant, or not trivially small, as well.

Specifically, these elasticities show that a 10% increase in the latent variable results in a 3.4% decrease in banana demand. Based on the index values shown in figure 2, such an increase in the latent variable can occur in a relatively short period of time -- from 1987 to 1992, for example, the index increased by almost exactly 10%. On the other hand, the elasticities of fresh apple and other fruit demand with respect to the latent index is nearly the same strength, but in the opposite direction. If changing tastes and information cannot explain the observed increase in demand, then price and expenditure effects must. The elasticities in table 3 show that bananas are

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both more price elastic and income elastic than apples.[7] Because the relative price of bananas to apples dropped by 1.4% over the sample period, this difference can perhaps explain some of the observed change in banana demand. However, other fruit, as a group, is more price elastic than bananas. The fact that banana prices dropped only 0.6% relative to the composite price of other fruits does little to explain the relative change in demand between these two products. Of more importance, however, is the expenditure elasticity. Total expenditure on fresh fruit increased by exactly 400% over the sample period. Other fruits, with an expenditure elasticity of 2.05, clearly benefit from increased fruit spending. Moreover, the expenditure elasticity of bananas is 50% higher than for apples, so this fact may be responsible for some of the observed change in demand. Notice also that virtually all pairs of products appear to be gross complements.

Although such results are often disregarded as evidence of a misbehaved demand system, their recurrence in the fruit demand literature suggests that they are more likely a reflection of actual consumer behavior (Lee, Brown, and Seale; Lee, Seale, and Jierwiriyapant). Gross complementarity will occur if a positive income (expenditure) effect resulting from a price reduction of one product outweighs the negative substitution effect. In other words, if consumers have a relatively fixed amount that they allocate to fresh fruit, then price reductions in one product will allow them to buy more of another product.[8] The result is a negative cross-price elasticity. This effect is strongest in the case of banana consumption as a 1% decrease in the price of other food causes a 0.55% increase in the demand for bananas. Investigating whether or not these gross complements are indeed net complements as well may help to explain these seemingly counter-intuitive results.

Table 4 shows the compensated, or Hicksian price elasticities. As expected, many of the pairs found to be gross complements do not remain net complements. In fact, only apples and oranges remain statistically significant net complements. More importantly, both apples and other fruit become net substitutes for apples. Because the relative price of bananas falls with respect to both of these alternative products, the reasons for the observed changes in banana consumption (figure 1) become more clear. Ultimately, however, the structure of demand among these fruits appears to be most sensitive to changes in the unobservable factors accounted for by the latent variable, so changes in its value over time are of considerable interest.

Figure 2 shows how the latent variable index changes over the sample period. Being able to place numerical values on changes in unobservable demand factors is unique to the DYMIMIC approach. While most studies of structural changes in demand are only able to estimate a single parameter or set of parameters, this model allows for a quantification of those effects that other studies only provide indirect evidence of. As an index, however, it is only changes in the latent variable value that are meaningful. Normalizing the index at 100 in 1951, the index has increased by 26% over the sample period, for an average annual gain of 0.59. If all changes in fresh fruit demand could be explained by variation in prices and expenditure, then this index would be constant. Therefore, finding such a sustained rise in the index suggests that there are other factors in the broader economy that are affecting the demand for fruit. Here we argue that these other factors are a composite of changing tastes and consumer information. The extent to which the index is affected by each of these factors is given by the parameters of the cause, or transition equation.

These parameters are shown in table 1. Surprisingly, both types of promotion have a negative effect on the latent variable, although only direct advertising is significant at conventional levels. With promotion program evaluation mandated by the Food and Agricultural Improvement and Reform Act in 1996, there are now a number of studies that purport to demonstrate the effectiveness of generic fruit promotion (Erikson et al., Alston et al.). However, the results of this paper suggest that accounting for other factors that explain changes in demand may reduce the apparent effect of promotion. Given that the latent variable increases monotonically over the sample period, as have promotion budgets, it may be the case that such positive promotion effects are the result of spurious correlation. To the extent that promotion efforts are *intended* to change tastes and to add to consumer information, however, the fact that past values of the latent index are significant suggests that this variable has more of a generic than a product-specific effect using the logic developed in the introduction to the paper. Consequently, the significance of direct advertising supports the contention that it has more of a persistent effect on demand, whereas retail promotion is used more as a "tactical" marketing tool with more short-term effects.

Because the latent variable rises over the sample period, the insignificance of promotion suggests that the rise is largely determined by the trends underlying changes in fast food consumption and the aggregate fat:carbohydrate ratio. In the former case, a rise of one percent in the proportion of food consumed as fast food causes the index value to rise by 0.034, an effect which is likely due to an increase in the demand for convenience in meal consumption and preparation. In terms of the parameters of table 1, the fat:carbohydrate coefficient suggests that a similar rise in the percentage of fats to carbohydrates in the diet causes the latent variable to rise by over 3.6 points. While this variable likely captures the trend towards, and then away from low

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fat diets over the sample period, it may also reflect the quality of nutritional information available to consumers. Whereas health officials argued for strict low-fat diets during the 1980s, more recent recommendations have advocated moderation and dietary balance.

Conclusions and Implications

Dramatic changes have occurred in the structure of fresh fruit demand since the early 1950s. Whereas banana and specialty fruit consumption have risen sharply, apple consumption has been largely flat, and fresh orange consumption has fallen markedly. These changes can be due to either price and income effects, socio-economic trends, or active promotion by fruit marketers. Promotion itself can also have different effects depending upon whether it is oriented towards the consumer, or to the distribution channel. This study considers the role of each in a Dynamic Multiple Indicator-Multiple Cause (DYMIMIC) model of fresh fruit demand.

The DYMIMIC framework is the most general form of structural latent variable model. As such, it defines a latent, or unobservable quantity measuring the stock of knowledge, or the state of tastes. Indicators of this latent variable consist of the proportion of women in the work force and fresh fruit budget shares derived from a LAIDS model. As a state-space model, equations relating these indicators to the latent variable form 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 and smoothing algorithm. Including an aggregate fat:carbohydrate consumption ratio, the percentage of food consumed as fast food, and direct advertising and retail promotion of Washington apples in the set of cause variables allows

the model to test for the contribution of promotion expenditures to changing tastes, and thereby changing demand, for different fresh fruits.

The fresh fruit DYMIMIC model, including apples, bananas, oranges, other fresh fruit, and other food, is estimated with annual data from 1951-1994. The results show that the latent variable has a significant effect on influence on the demand for apples, bananas, other fruit, and other food. The latent index has a positive effect on apple, other fruit, and other food demand, while reducing the demand for bananas. In the cause equation estimates, both fast food and the fat:carbohydrate ratio have a positive effect on the latent variable value, while direct advertising has a significant negative effect. Retail promotion, on the other hand, has no statistically significant effect. This suggests that taste changes dominate the latent information effect of advertising, and that advertising, in turn, has a stronger effect on consumers' buying habits than does retail promotion. The significance of the lagged latent variable in this equation, however, implies that however consumer preferences are formed, they tend to persist.

Future research in this area can extend along many lines. First, a data set with more observations would 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 in this direction. Third, specifying a two-stage demand system would allow the estimation of both product-specific and fruit-category price, expenditure, and latent variable elasticities. A fourth area for improvement concerns the nature of the USDA consumption data. Adjusting the published "per capita consumption" figures, which are, in fact per capita utilization, for net exports and storage

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will more closely approximate the true amount that is 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, the amount of time spent in leisure activity are but a

few of the alternatives deserving consideration.

Endnotes

1. Information, in this context, is defined broadly enough to include product characteristics, price, location, availability, quality, or any other factor that may help a consumer arrive at a decision that more accurately reflects their true preferences.

2. See Cox for a review of these approaches taken to incorporate promotion dynamics into empirical models.

3. While this ratio fell throughout the 1980s, in recent years the relative amount of fat calories available for consumption has risen sharply (Center for Nutrition Policy and Promotion).

4. While other apple promotion agencies exist, they comprise only 31% of the market in 1994. Further, neither these agencies nor sellers of fresh oranges (Sunkist) or bananas (Dole, Chiquita, Pacific Fruit) would provide promotion data for the 1951-94 period.

5. As a reviewer notes, Alston and Chalfant present results that favor a Rotterdam over a LAIDS specification in their data. Veeman and Xu, however, find that their Canadian meat demand data reject a Rotterdam in favor of an AIDS specification. Further, Alston and Chalfant show very little difference in demand elasticities between the two functional forms. Similar tests could not be performed here, however, as attempts to estimate a differential Rotterdam model within the DYMIMIC algorithm failed to converge.

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

7. These price elasticities are calculated assuming constant shares using the expression that is appropriate for the LA/AIDS is given as:
$$\epsilon_{ij} = -\tau_{ij} + (\gamma_{ij} - \beta_i w_j)/w_i; \quad \tau_{ij} = 1 \; \textit{if } i = j; \quad \tau_{ij} = 0 \; \textit{if } i \neq j.$$
and the expenditure, or scale, elasticity by:
$$E_i = -1 + \beta_i/w_i.$$

8. This logic is more intuitive if purchases are viewed in a household production framework (Stigler and Becker). If households do not buy fruit for their individual consumption, but to satisfy a need to meet specific nutritional goals (such as that advocated by the 5-A-Day program), then the non-market commodity that provides consumer utility (nutritious diets) can be comprised of any one of a number of market goods. In this sense, complementarity is to be expected as many uses of fresh fruit are combination-products such as fruit baskets, fruit cups, or fruit salads.

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Table 1. DYMIMIC Cause Parameter and Indicator Variance Estimates.

Cause	Estimate	t-ratio	Se(e_t)	Estimate	t-ratio
Advertising	-0.0759*	-3.4313	e_a	0.0062*	5.9054
Retail Promotion	-0.1009	-1.1805	e_b	0.0128*	6.3112
Fast Food	0.0338*	1.9592	e_o	0.0060*	6.1713
Fat:Carbo	3.6030*	1.8165	e_{of}	0.0107*	6.4215
Q	1.0578*	5.8962	**G**	2.0552*	5.1283
Ξ_{t-1}	0.6086*	2.5471			

A single asterisk indicates significance at a 5% level. The elements of the *e* vector reported here are standard errors for the disturbances in the indicator equations, where the disturbance for the "other food" equation is normalized to 1.0 for identification purposes. In the subscripts, a=apple, b=banana, o=orange, of=other fruit, ww=percentage of women in workforce. Q is the variance of the cause equation, and Ξ_{t-1} is the coefficient on the lagged latent variable. The GAUSS Kalman filter algorithm provides no goodness-of-fit measures beyond the system log-likelihood function value.

Table 2. DYMIMIC LA/AIDS Fresh Fruit Parameter Estimates: 1951-1994.

	Apples	Bananas	Oranges	Other Fruit	Other Food
P_{apples}	0.067*	-0.014	-0.015*	-0.025*	-0.006
	(10.921)	(-1.103)	(-2.489)	(-2.376)	(-0.809)
$P_{bananas}$	-0.007	0.184*	-0.024**	-0.023	-0.109*
	(-0.536)	(6.740)	(-1.874)	(-1.013)	(-6.092)
$P_{oranges}$	-0.014*	-0.001	0.014*	0.016	-0.032*
	(-2.020)	(-0.032)	(1.993)	(1.335)	(-3.435)
$P_{other\ fruit}$	-0.006	-0.014	-0.009	0.049*	0.156*
	(-0.578)	(-0.572)	(-0.824)	(2.342)	(5.131)
$P_{other\ food}$	-0.033	-0.131*	0.018	-0.019	-0.046*
	(-1.515)	(-2.886)	(0.826)	(-0.503)	(-2.706)
M	-0.011	0.058*	0.052*	0.150*	-0.273*
	(-0.771)	(2.008)	(3.825)	(6.222)	(-14.096)
Ξ	0.021*	-0.096*	0.003	0.034**	0.007*
	(1.996)	(-4.298)	(0.276)	(1.809)	(4.784)
R^2	0.863	0.946	0.766	0.596	0.956

Variable definitions: M = total expenditure; Ξ = latent variable; P_i = retail price index of each product. T-ratios are in parentheses. A single asterisk indicates significance at a 5% level, a double asterisk at 10%. The value of the log-likelihood at its optimal value is 7.1366. The reported R^2 value is the square of the correlation between observed and predicted share values.

Table 3. DYMIMIC LA/AIDS Fresh Fruit Elasticities: 1951-1994.

	Apples	**Bananas**	**Oranges**	**Other Fruit**	**Other Food**
P_{apples}	-0.2418*	-0.0689	-0.2889*	-0.2711*	0.0444*
	(-3.6354)	(-1.4782)	(-3.3076)	(-3.7366)	(2.6259)
$P_{bananas}$	-0.0446	-0.4015*	-0.5665*	-0.4549*	-0.0797*
	(-0.3201)	(-3.9498)	(-3.1454)	(-3.013)	(-1.9463)
$P_{oranges}$	-0.1433*	-0.0159	-0.8547*	0.0373	-0.0306
	(-1.9402)	(-0.3138)	(-8.6803)	(0.4768)	(-1.4078)
$P_{other\ fruit}$	-0.0598	-0.0807	-0.2519	-0.8088*	-0.3553*
	(-0.4537)	(-0.8917)	(-1.4809)	(-5.6389)	(-5.0956)
$P_{other\ food}$	-0.3143	-0.5533*	-0.0581	-0.5709*	-0.0156
	(-1.3566)	(-3.3054)	(-0.1906)	(-2.2606)	(-0.3950)
M	0.8808*	1.2071*	1.7601*	2.0496*	0.3477*
	(5.6883)	(11.6998)	(8.8539)	(12.1620)	(7.5046)
Ξ	0.2351*	-0.3409*	0.0409	0.2370*	0.0169*
	(1.9906)	(-4.3018)	(0.2772)	(1.8128)	(4.7333)

Variable definitions: M = total expenditure; Ξ = latent variable; P_i = retail price index of each product. A single asterisk indicates significance at a 5% level. The price elasticities in this table are uncompensated.

Table 4. DYMIMIC LA/AIDS Compensated Fresh Fruit Price Elasticities: 1951-1994.

	Apples	Bananas	Oranges	Other Fruit	Other Food
P_{apples}	-0.1632*	0.2021*	-0.0834*	0.0673	0.0546
	(-7.9941)	(4.6236)	(-3.7169)	(1.6514)	(1.7559)
$P_{bananas}$	0.0392	-0.0635	0.0678*	0.0921	-0.0484
	(1.6314)	(-1.8286)	(2.5011)	(1.9475)	(-0.5591)
$P_{oranges}$	-0.1314*	-0.0732	-0.7341*	0.0021	0.6798*
	(-5.6143)	(-1.4929)	(-2.8244)	(0.5378)	(8.2213)
$P_{other\ fruit}$	0.0591	0.3857*	0.0712*	-0.7802*	0.2748*
	(1.4637)	(7.7032)	(2.1456)	(-8.5564)	(2.7311)
$P_{other\ food}$	0.0766*	0.0183	-0.0489	0.0347	-0.0209*
	(6.7089)	(1.6341)	(-0.4795)	(1.3132)	(-4.4778)

See table 3 for variable definitions. A single asterisk indicates significance at a 5% level. The compensated price elasticities are calculated at variable means using the formulas:

$$\varepsilon_{ij} = -\tau_{ij} + \gamma_{ij}/w_i + w_j; \quad \tau_{ij} = 1 \; if \; i = j, \quad \tau_{ij} = 0 \; if \; i \neq j.$$

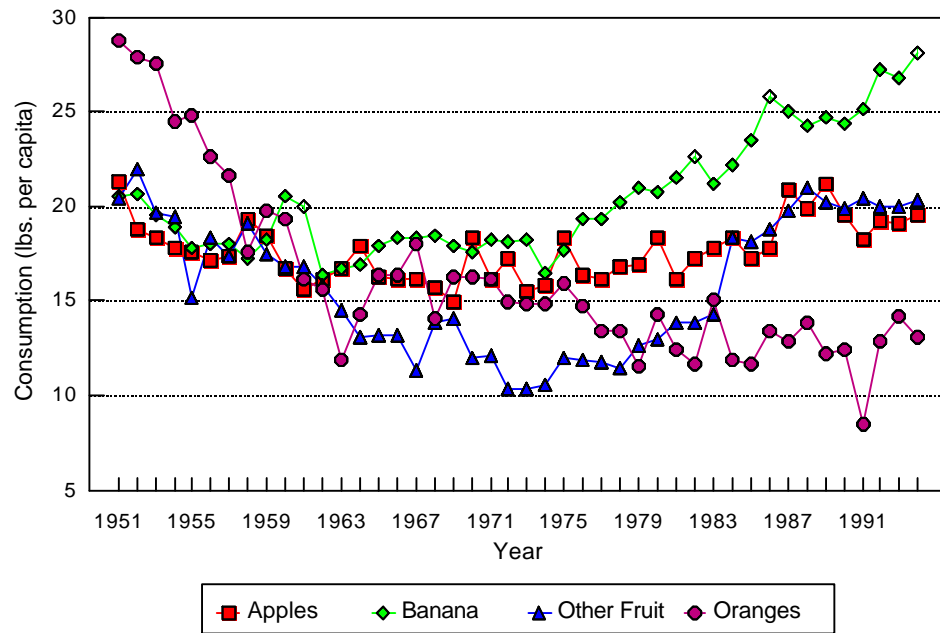**Figure 1.** U.S. Per Capita Fruit Consumption, 1951-1994.

Figure 2. Latent Fresh Fruit Taste and Information Index Variable, 1951-1994.