Is the Efficacy of Agricultural Promotion Programs Overestimated? The Importance of Dynamics in Advertising Demand Systems

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IS THE EFFICACY OF AGRICULTURAL PROMOTION PROGRAMS OVERESTIMATED? THE IMPORTANCE OF DYNAMICS IN ADVERTISING DEMAND SYSTEMS†

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Abstract

This article outlines the shortcomings of current techniques to assess the effectiveness of agricultural commodity promotion campaigns; particularly their neglect of the dynamic nature of the underlying demand system. The dynamics that affect advertising effectiveness over time are illustrated, and the importance of cointegration in commodity markets is outlined. A dynamic, error-correction Almost Ideal Demand System is developed to accommodate the aforementioned dynamics and this model is applied to US meat data. Short and long-run elasticities for the dynamic model using Stone's price index are derived and estimated. The article also includes a discussion of the use of elasticities in policy decisions.

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†First draft. Please do not quote.

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Introduction

Measuring the effectiveness of advertising is one of the most active research areas in agricultural economics. The large sums of money, both private and public, spent on agricultural promotion are testaments to the importance of accurately assessing its effectiveness. Hayes estimates that if US$500 million is spent each year on promotion programs, then the average cost to farmers is US$1000. Such programs are often mandatory, in that producers of a promoted good must contribute to the marketing program through a “check-off” system. That, combined with the fact that public funds make up a large share of agricultural promotion programs, heightens the public interest in accurate appraisals of promotion programs.

The majority of attempts to assess advertising effectiveness do so by estimating demand equations or systems and testing the impact of advertising expenditures. Results from such analyses are inconsistent and disappointing. Different functional forms yield different conclusions using similar data, and elasticity estimates are frequently counterintuitive. Furthermore, static demand-based studies overlook dynamic market interactions that can influence the effectiveness of advertising over time. This article outlines the dynamics that may unfold over time, which can alter the effectiveness of advertising expenditures. These dynamics are incorporated into an empirical model that is applied to US meat data.

Commodity Promotion and Assessing its Effectiveness

Generic advertising describes promotional activity in markets that are comprised of homogenous, highly substitutable products. Often, such products are not branded, so consumer tastes do not dictate choosing one variety over another. The benefits (measured in terms of higher prices) of generic advertising are therefore non-excludable to producers of substitutable commodities that have not invested in advertising. As such, no individual producer has incentive to advertise his product independently of other producers of close substitutes. Generic advertising therefore has some characteristics of a public good. The result can be an underinvestment in commodity advertising.

Because benefits are non-excludable, generic and commodity advertising is usually undertaken by an association of commodity producers. Federal marketing orders compel all producers to contribute funds to their respective associations. Contributions are often mandatory in an effort to avoid the free-rider problem and to correct for the perceived underinvestment in advertising.

There are several methods that have been used to analyse the effectiveness of commodity promotion. A detailed critique of each method is beyond the scope of this article. However a brief mention of the important contributions of some of the methods is worthwhile, for the goal of this article is to harness the best techniques of various methods and add to them to produce a better assessment tool.

Single-equation structural demand equations are a popular method and remain in use for two primary reasons. The first is that demand for each good can be modeled independently to include just those variables deemed necessary to determine demand for that good. A second advantage is computational ease.

Another method, developed by Kinnucan, evaluates the effects of advertising on interrelated markets using a Muth-type disequilibrium model[i] that includes advertising as an exogenous variable. The main insight of Kinnucan's model is its recognition of the importance of product substitutability in determining the effectiveness of advertising. Specifically, a positive own-advertising elasticity is no guarantee that advertising increases own price. The results depend on the size of price, cross-advertising and supply elasticities.

Demand systems have become economists' favourite method for estimating the effects of advertising. System methods allow demand for a group of separable goods to be estimated together, while accounting for the substitution effects that Kinnucan outlines in his disequilibrium model.

System models possess several advantages. The first is that the introduction of information variables does not compromise the system's theoretical integrity. A second reason for analysing advertising within the context of a system is that estimation is done using system econometric techniques. Such a setting is ideal for examining the cross-price and cross-advertising effects on substitutable goods within a weakly separable group. Hayes notes that estimating advertising effects in a system does impose a particularly strict constraint, however. Specifically, if the budget constraint is binding, then a zero-sum game is imposed. An advertising-induced increase in demand for one good must be offset by a corresponding decrease in demand for another good(s) in the estimated separable group.

A more recent approach to evaluate the effects of advertising uses time-series econometrics. Cavaliere and Tassinari test for long-run causality relationships between advertising and demand by means of a vector error correction (VEC) model. The primary contribution of this technique is to recognise the important time-series properties of the data used in estimation.

It should be noted that all of the aforementioned methods (other than VEC analysis) neglect the time-series properties of the relevant data. The accurate modelling of the dynamic properties of the estimated data is particularly important in commodity advertising studies. The time-series behaviour of prices in a demand system can provide important insight into the effects of advertising in that market. This point is discussed in the next section.

This article develops a model that captures the beneficial aspects of the aforementioned methods, while attempting to minimise the drawbacks. The model is a demand system, so as to take advantage of desirable econometric properties and remain consistent with consumer theory. It also considers and models the time-series properties of the data.

Model

Deaton and Muellbauer's Almost Ideal Demand System (AIDS) is a researcher favourite in applied economics. It is the ability to introduce exogenous information variables, as well as its consistency with consumer optimisation behavioural assumptions, that have made the AIDS such a popular research tool.

The AIDS model is derived from the PIGLOG class of cost functions[ii], which defines the minimum expenditure required to attain a given level of utility at fixed prices. The derived estimable share equations are

(1) $$w_i = \alpha_i + \sum_j \gamma_{ij} \ln p_j + \beta_i \ln\left\{\frac{X}{P}\right\}$$

where w_i represents good i's budget share, p_i s are prices, X is total group expenditure and P is a price index defined by

(2) $$\ln P = \alpha_0 + \sum_k \alpha_k \ln p_k + \frac{1}{2}\sum_j \sum_k \gamma_{kj} \ln p_k \ln p_j$$

Three groups of parameter restrictions are imposed when estimating (1) to ensure theoretical consistency.

(3) $$\sum_{i=1}^{n} \alpha_i = 1 \qquad \sum_{i=1}^{n} \gamma_{ij} = 0 \qquad \sum_{i=1}^{n} \beta_i = 0$$

These restrictions ensure that budget shares to one (i.e. $\sum_{i=1}^{n} w_i = 1$).

(4) $\sum_{j=1}^{n} \gamma_{ij} = 0$ ensures that the demand functions are homogenous of degree 0.

(5) $\gamma_{ij} = \gamma_{ji}$ guarantees Slutsky symmetry of cross partial price derivatives.

It should be noted that the AIDS, as outlined above, is nonlinear in parameters. It is common practice to replace (2) with Stone's linear approximation, defined as

(2a) $$\ln P^* = \sum_k w_k \ln p_k$$

The most common (see Piggott et al., Rickertsen et al, and Boetel and Liu for examples) method of incorporating advertising into an AIDS model is to allow advertising expenditures to affect a base level of consumption. The estimable share equations are

$$(6) \qquad w_i = \alpha_i + \sum_j \gamma_{ij} \ln p_j + \beta_i \ln\left\{\frac{X}{P}\right\} + \sum_j \delta_{ij} \ln A_j$$

Demand systems are dynamic in nature. Advertising campaigns are unveiled over several periods, and consumers and producers react with lagged responses. Market dynamics such as shifting demand and supply and their subsequent effects on prices unfold over time, making the problem of analysing advertising effectiveness a dynamic one.

As such, investigating the time-series characteristics of the variables in a demand system is important for two primary reasons. First, most economic time-series data are non-stationary and must be modelling accordingly. Ignoring the time-series properties of data when estimating regression relationships can result in *spurious* regressions (Granger and Newbold). If variables in a system are nonstationary, then cointegration between them must be investigated.

The establishment of cointegration between variables provides information that is valuable in estimating a structural relationship. In fact, if a group of variables is cointegrated, then estimating a structural relationship without accounting for the long-run dynamics amounts to a serious specification error (Enders). If a group of variables share a long-run equilibrium, then the variables' short-term dynamics should be, in part, influenced by the variables' relationships to their long-run equilibrium. Correcting for such misspecification should improve model performance.

Error-correction (EC) models accommodate the influence of a long-run equilibrium relationship on short-term dynamics. Once a cointegrating relationship between variables is estimated, then each period's deviation from the long-run equilibrium can be calculated. This deviation, called the EC term, can then be introduced into a regression equation that explains a variable's short-run dynamics. Intuitively, if a system of cointegrated variables is out of equilibrium in period t, then the system should respond in period $t+1$ to move the system towards the long-run equilibrium.

Beyond correcting for misspecification errors, the existence of a long-run relationship between variables provides insight into the intra-market dynamics between substitutable products. This section outlines the importance and identification of these dynamics.

Advertising expenditures are made with the intention of providing consumers with information that change their tastes, thereby shifting out the demand curve. The goal is a higher price and higher profitability. Shifting out the demand curve is, however, contingent on the ability to differentiate one's product from close substitutes. Differentiating among a group of goods that includes, say, different brands of cars may be feasible. Even though such goods are often treated as a weakly separable group in demand systems, their characteristics differ enough that price is not the only differentiating factor. Certain groups of close substitutes, however, may not be so differentiable. Consumers may be readily willing to substitute one good for another based primarily on relative price changes. Such nearly homogeneous goods that cannot be differentiated from each other are often defined as commodities.

If products fit into such a categorisation then one would believe, *a priori*, that marketing programs intended to shift out the demand curve would be difficult propositions. Even if an advertising campaign were successful in increasing a commodity's price in the short run by shifting out the short-run demand curve, market forces would act to bring its price back in line with those of its close substitutes.

In particular, if a commodity's price rises (as the result of a marketing campaign) relative to close substitutes, then price competition from substitutes eventually erodes demand for the promoted product. Static supply and demand graphs are not entirely adequate tools for analysing the relevant dynamics, but some key points can be gleaned from graphical comparative statics. Consider figure 1. The initial equilibrium is characterised by price P^0 and the corresponding short and long-run demand and supply curves. If a producers' association initiates an advertising campaign for their product, new costs will be imposed on producers, shifting the supply curves to retail up to S^1_{SR} and S^1_{LR}. If the advertising campaign is successful in affecting consumer tastes, then demand curves shift up to D^1_{SR} and D^1_{LR}. The new short-run equilibrium price is P^1. Over the long-term horizon, however, price competition from close substitutes will pare away at demand for the promoted product. This is represented by a more elastic long-run demand curve. Long run price settles at P^2, where long-run demand and supply intersect.

The dynamics described above are a different phenomenon from advertising *wearout*. Advertising wearout (as analysed by Kinnucan, Chang and Venkateswaran) describes how advertising loses effectiveness over time because consumers become less responsive to promotional information and can affect a product with no substitutes. Consider a theoretical product that undergoes an advertising campaign that is successful in altering consumer tastes and shifting up short-run demand. If this campaign varies over time and is able to prevent wearout, then consumer tastes will not change back to their pre-advertising state. Long-run demand will shift up along with short-run demand.

The effects of advertising wearout can be illustrated in figure 1. The initial advertising campaign alters consumer tastes and shifts short-run demand from D^0_{SR} to D^1_{SR}. Short-run equilibrium price is P^1. Note that long-run demand does not shift in the case of advertising wearout because the initial change in consumer tastes "wears off" over the long-term horizon. Long-run supply does, however, shift up to reflect the advertising levy imposed on producers. Once the effects of advertising wearout have taken hold and consumers have had the opportunity to adjust their spending patterns to account for cheaper substitutes, the long-run equilibrium price of P^3 prevails at the intersection of D^0_{LR} and S^1_{LR}.

Supply-side market dynamics can also render advertising less effective over the long-term horizon. Refer again to figure 1, where the industry begins at price P^0 and zero profts. An advertising campaign successfully shifts short-run demand up and leads to higher prices (P^1) and profits. Assuming low entry barriers, profit opportunity is a signal for firms to enter the industry. Firms will enter, which is reflected by the relatively elastic long-run supply curve. Price falls back to P^2 over the long-run horizon (or back to P^3 if there is advertising wearout).

Another possibility is that a promotional campaign successfully differentiates the promoted product from its substitutes, resulting in a permanent demand shift. For example, a crop may be found to have beneficial health attributes over and above its substitutes.

The static illustrations outlined above provide some insight into the starting and ending points for the dynamic process under consideration. However they do not impart any understanding of the path from one static equilibrium to the next. The empirical portion of this article estimates the effect on demand of moving from the initial equilibrium to a long-run post-advertising equilibrium.

The question facing policy makers is how to determine if a product can be categorised as a commodity. If it can, then it stands to reason that increasing profits over the long-run horizon is difficult by means of marketing. As Gordon, Hannesson and Kerr point out, a workable commodity definition is required for an adequate appraisal of an advertising campaign's probable success. Commodities are generally thought to be homogeneous and interchangeable, however a simple assertion that a product fits these characteristics may not be sufficient. Gordon et al provide an insightful solution. If markets for multiple goods are related as substitutable commodities, then there should exist a long-run equilibrium relationship between their prices. That is, prices for substitutable commodities should be cointegrated with each other. If the price of a cointegrated commodity deviates from its long-run equilibrium relationship with other commodity prices, then market forces return that price to its equilibrium course.

The prospect of a cointegrated equilibrium among prices begs the question of whether static demand-based studies of advertising effectiveness produce shortsighted conclusions. Consider a static AIDS model that estimates significantly positive advertising elasticities for a given product in a given spatial market. It seems possible that such studies are capturing the initial shift in demand that leads to a higher price (as illustrated in figure 1).

If the market dynamics are as illustrated in figure 1 (ie: the advertised good is a commodity), however, then the price shock may be transitory. The price eventually returns to its cointegrated equilibrium course and profits are eroded. Since most promotional programs involve a long-term financing commitment from participants, costs may overtake benefits as market dynamics unfold.

Having established the importance of identifying the dynamic properties of the data, the next step is to apply EC techniques to the AIDS models described above. The next section develops the advertising-augmented EC AIDS model.

If the data used in the model are nonstationary, then an error-correction model (ECM) should be pursued. An ECM's long-run elasticities provide estimates of how consumption responds to an advertising shock after the long-run equilibrium is attained. This last point is key in the case of commodities. Only the long-run advertising elasticities from an ECM relate how demand responds to advertising after the 'dust has settled' from the dynamics outlined in figure 1.

The AIDS specification from above is enhanced as an EC model:

(7) $$\Delta w_{it} = \alpha_i + \pi_i \Delta w_{it-1} + \sum_j \gamma_{ij} \Delta \ln p_{jt} + \beta_i \Delta \ln\left(\frac{X}{P}\right) + \sum_k \delta_{ik} \Delta \ln A_{kt} + \lambda_i \mu_{t-1}$$

All variables in equation (7) are as previously defined, and are stationary in the EC form. μ_{t-1} is the lagged EC term which represents the deviation from the cointegrated variables' long-run equilibrium in period $(t-1)$. The contemporaneous change in w_i responds to this deviation according to the parameter λ_i.

At this point, it is worth noting the difference between an EC-specified AIDS model and a dynamic adjustment AIDS model. A dynamic adjustment AIDS model (see Anderson and Blundell (1984) or Burton and Young for applications of such a model) can be similar to equation (7) but instead of the EC term μ_{t-1}, the Anderson and Blundell (1982) version of a dynamic demand system includes the adjustment term $(\hat{w}_{it-1} - w_{it-1})$. $\hat{w}_{it-1}$ is the predicted value of demand share in period $(t-1)$, which is formulated by a static demand system (like equation (1)). The current change in share, Δw_i, is a function of current exogenous variables as well as the disequilibrium between the predicted share in period $(t-1)$ and the observed share in period $(t-1)$. Underlying this model is the assumption that there exists a steady-state relationship that can be represented by the standard AIDS system of equation (1). Any deviation from this steady-state influences the movement of shares in future periods.

There are two key differences between the Anderson and Blundell dynamic adjustment AIDS model and an EC-specified AIDS model. First, dynamic adjustment models do not necessarily test for and accommodate the time-series properties of the underlying data. Also, dynamic adjustment models do not explicitly test for cointegrating relationships between nonstationary variables. The steady-state relationship of (1) is imposed and any deviation from that state is presumed to be a disequilibrium. Modern econometric techniques allow for the explicit testing and estimation of cointegrating relationships.

Application

This section applies the EC advertising-augmented AIDS model of the previous section to US meat (beef, poultry, pork and fish) data. The meat industry is a logical choice for this type of study. Most meat advertising is generic, and is initiated at the producer level. Since most meat marketing is done at the producer level, it would seem that producers view their products as homogenous. Such products might be categorised as commodities.

Another reason to analyse meats in this model is that supply is flexible. Several models that investigate the effectiveness of advertising are applied to supply-managed agricultural industries. Meat output is not regulated, so profit opportunities can be followed by entry and increased supply over the long run.

The meat data for this study were graciously provided by Professor Brenda Boetel of The University of Wisconsin, River Falls. It comprises quarterly data, from 1976 to 1993. Price and consumption data are from Putman and Allshouse and USDA's *Livestock and Poultry Situation and Outlook Report*. Fish consumption data are from the USDA's Economic Research Service, Food Consumption Data System. Advertising expenditure data were obtained from *AD $ Summary*, published by the Leading National Advertisers. Beef and pork advertising expenditures are those reported by the Beef Industry Council and the National Pork Producers Council.

Advertising expenditures are deflated using the US Bureau of Labour Statistics Consumer Price Index. To account for the development of a stock of advertising knowledge and awareness, advertising expenditure is a three-quarter weighted average, with weights of 30-40-30 (Boetel and Liu).

The first step is to establish the time series properties of the data. Specifically, all series must be tested for unit roots. If a unit root is found in any of the series, then the demand estimation strategy must reflect the data's nonstationarity. The stepwise methodology developed in Enders is followed for Augmented Dickey-Fuller tests. The non-standard Dickey-Fuller test statistic is needed only when deterministic regressors that are not in the actual data-generating process. To ensure that the appropriate test statistic is used, Enders recommends a stepwise procedure that begins with the least restrictive form (i.e. with a drift and trend) and then pares the test equation down as allowable.

The stepwise procedure concludes that all series contain a unit root in levels. The results are robust to selection of lag length in equation and to significance level in null hypotheses testing. To ensure that all series are integrated of the same order, the same stepwise procedure described above is applied to all series in first-differences. Testing on all series produces the conclusion that all series are stationary in first-differences.

Cointegration between the nonstationary variables in the model is investigated using the Johansen procedure. The Johansen procedure estimates

(8) $$\Delta X_t = \pi X_{t-1} + \sum_{i=1}^{\rho-1} \pi_i \Delta X_{t-i} + U_t$$

where $\pi = -(I - \sum_{i=1}^{\rho} A_i)$ and $\pi_i = -\sum_{j=i+1}^{\rho} A_j$

If the rank of π is zero, then $\Delta X_t = U_t$, or $X_t = X_{t-1} + U_t$ and no linear combination of the variables in X is stationary. That is, the variables in X are not cointegrated. If, however, the rank of π is positive then there exists at least one linear combination of the variables in X that is stationary. So the rank of π is equal to the number of independent cointegrating vectors for the variables X. The Johansen procedure uses the fact that the rank of a matrix is equal to the number of characteristic roots that are not equal to zero. Characteristic roots are estimated, and then tested to evaluate how many are significantly different from zero. This provides the number of cointegrating vectors for the variables X. The Johansen estimation procedure produces characteristic roots, which are used in the following trace and max test statistics[iii].

The trace test statistic is calculated as

(9) $$\lambda_{trace}(r) = -T \sum_{i=r+1}^{n} \ln\left(1 - \hat{\lambda}_i\right)$$

and the null hypothesis is that there exist less than or equal to r cointegrating vectors versus a general alternative. The max statistic is calculated as

(10) $$\lambda_{\max}(r, r+1) = -T \ln\left(1 - \hat{\lambda}_{r+1}\right)$$

The null hypothesis for the max test is that there exist r cointegrating vectors versus the specific alternative of $r+1$ cointegrating vectors.

Both the trace and max tests concur that there exist three cointegrating vectors between the eight variables in the estimated system (four prices and four consumption shares[iv]). These cointegrating vectors are used to calculate the EC terms for subsequent estimation of the EC AIDS model. The EC terms are operationalised by calculating a deviation from long-run equilibrium for each period using the coefficients from the estimated cointegrating vectors. Each period has three different EC terms of the form

(11) $$\mu_t = a_1 \ln P_{bt} + a_2 \ln P_{ct} + a_3 \ln P_{ft} + a_4 \ln P_{pt} + a_5 w_{bt} + a_6 w_{ct} + a_7 w_{ft} + a_8 w_{pt}$$

where P_i and w_i are prices and shares for beef, poultry, fish and pork. One cointegrating vector, or EC term, is selected for estimation according to best fit.

The crux of this investigation is the estimation of the EC AIDS model. The strategy is to estimate the model in static non-EC form and derive short-run advertising and price elasticities. The dynamic, EC counterpart is then estimated and its long-run elasticities are contrasted with short-run elasticities. The estimated equations use Stone's price index with share lagged one period.

The estimated form, which is referred to as model I, is

(12) $$w_i = \alpha_i + \sum_{j=1}^{4} \gamma_{ij} \ln p_j + \beta_i \ln\left(\frac{X}{P^*}\right) + \sum_{k=1}^{2} \delta_{ik} \ln A_k$$ for i = beef, poultry, fish and pork; k = beef and pork

The system is estimated in Eviews by means of Zellner's seemingly unrelated regression (SUR) systems approach. One equation is dropped from estimation to avoid singularity of the covariance matrix since the equations sum to one by construction. The equation for pork demand is dropped and parameters are recovered using cross-equation restrictions outlined in (3) through (5). There is an additional adding-up cross-equation restriction in advertising-augmented AIDS models. To ensure that consumption shares add up to one, the restriction

$$(13) \qquad \sum_{i=1}^{n} \delta_{ij} = 0$$

is imposed.

The EC counterpart to (14), which is referred to as model I_{EC}, is

$$(14) \qquad \Delta w_i = \alpha_i + \pi_i \Delta w_{it-1} + \sum_{j=1}^{4} \gamma_{ij} \Delta \ln p_j + \beta_i \Delta \ln\left(\frac{X}{P^*}\right) + \sum_{k=1}^{2} \delta_{ik} \Delta \ln A_k + \lambda_i \mu_{t-1}$$

and is also estimated by iterative SUR. Parameter estimates, t-stats and R^2 are reported in table 1.

Most of the discussion of results focuses on elasticise, however it is interesting to note the change in the significance of the advertising coefficients (δ_{ij}) between model I and model I_{EC}. The t-stats for all advertising coefficients fall substantially in the EC model. The statistical significance of advertising expenditure's effect on consumption shares is smaller when modelled in dynamic EC form than in static form.

Advertising elasticities for these models must be derived under the consideration that the AIDS models are estimated using Stone's price index. Using standard AIDS elasticity formulae is a common error in empirical demand analysis that utilises Stone's price index (Green and Alston). This section uses the correct price elasticity formula derived by Green and Alston and applies this methodology to derive advertising elasticities.

Define $\varepsilon_{ij} = \dfrac{d \ln q_i}{d \ln A_j}$ as the elasticity of demand for good *i* with respect to advertising expenditure on good *j*. In the case of specification I, this is

$$(15) \qquad \varepsilon_{ij} = \frac{1}{w_i}\left(\delta_{ij} - \beta_i \frac{d \ln P^*}{d \ln A_j}\right)$$

The derivative of the price index in the standard AIDS model is a linear function of parameters. The derivative of Stone's price index is more complicated. Specifically,

$$(16) \qquad \frac{d \ln P^*}{d \ln A_j} = \sum_k w_k \ln p_k \varepsilon_{kj}$$

Plugging this into (15) gives

$$(17) \qquad \varepsilon_{ij} = \frac{1}{w_i}\left(\delta_{ij} - \beta_i \sum_k w_k \ln P_k \varepsilon_{kj}\right) = \frac{\delta_{ij}}{w_i} - \frac{\beta_i}{w_i} \sum_k w_k \ln P_k \varepsilon_{kj}$$

Each elasticity ε_{ij} is a function of itself and all other elasticities. Equation (19) can be expressed in matrix form and solved for elasticities using linear algebra.

$$(18) \qquad E = A - BCE$$

where E is a (4 X 2) matrix containing elements $e_{ij} = \varepsilon_{ij}$, A is a (4 X 2) matrix with elements $a_{ij} = \frac{\delta_{ij}}{w_i}$, B is a (4 X 1) matrix with elements $b_i = \frac{\beta_i}{w_i}$ and C is a (1 X 4) matrix with elements $c_j = w_j \ln P_j$.

Equation (18) can be solved for E as:

$$(19) \qquad E = (I + BC)^{-1} A$$

Price and advertising elasticities are calculated in two steps. First, the aforementioned methodology is used to compute short-run elasticities for models I and I_{EC}. The second step calculates long-run elasticities for model I_{EC} according to

$$(20) \qquad \varepsilon_{ij}^{LR} = \frac{\varepsilon_{ij}}{(1 - \pi_i)}$$

Elasticities are reported in table 2 and price elasticities are uncompensated.

The short-run elasticities from model I and model I_{EC} reflect the effect on quantity demanded of the advertising-induced short-run demand and short-run supply shifts. This initial movement is characterised in figure 1 by the movement of the point at P^0 to that at P^1. The short-run own-price elasticities are of the expected (negative) sign and of a reasonable magnitude in the static model I. Cross-price elasticities are mixed, with some negatives. This implies complimentarity between meats. Own short-run price elasticities from model I_{EC} are mostly negative, with the exception of fish. The EC model also produces larger (with the exception of fish) own-price elasticities than does the static model. Like in model I, there are some negative cross-price elasticities.

Long-run elasticities from model I_{EC} reflect how quantity demanded responds to advertising expenditure once the long-run equilibrium has been attained. In figure 1, this is at the intersection of the long-run demand and long-run supply curves. The long-run price elasticities from model I_{EC} do not all correspond with the expection that long-run price elasticities are larger than their short-run counterparts. The long-run estimates from model I_{EC} are larger than those from the static model, but only pork's own-price elasticity exceeds the short-run estimate from model I_{EC}.

The advertising elasticities in model I include several counterintuitive results. Specifically, the model produces a negative own-advertising elasticity for beef and several positive cross-advertising results. The short-run advertising elasticity estimates are more in line with theoretical expectations when the EC methodology is applied. Model I_{EC} contains all positive own-advertising and mostly negative cross-advertising elasticities. Also, most elasticities are smaller in model I_{EC} that in the static model I. The primary difference between the short and long-run elasticities estimates is that the long-run own-advertising pork elasticity is considerably higher than its short-run counterpart.

Remarks on Elasticities

Elasticities are the common yardstick for determining if advertising "works". Demand systems are estimated, elasticities computed and policy decisions made according to those elasticities. There are several reasons, however, to exercise caution when evaluating elasticities.

First, like in any empirical economic study, the *ceteris paribus* conditions are difficult to enforce. One would hope that a properly specified demand equation controls for all relevant variables that affect demand. This is never the case. Misspecification affects parameter estimates and attributes either too much or too little influence to some or all of the independent variables in the system. For example, an exogenous shock that increases beef demand and coincides with an advertising campaign for beef attributes too much credit to advertising if the exogenous shock is not in the demand system. Demand systems already consist of several variables, and the benefits of including more exogenous variables must be balanced with the benefits of econometric parsimony.

Elasticities are based on these imperfect parameter estimates and must be understood in this context. Elasticities can be considered, at best, a crude estimation of the direction and magnitude of an independent variable's effect on a dependent variable. As such, one must avoid deriving overly-fervent conclusions. For example, Chang and Green state that "consumers respond...negatively to advertising for dairy products..." based on negative own-advertising elasticities for dairy. This statement implies that consumers view dairy advertisements and consciously decide to decrease their consumption of dairy products in response. This seems implausible. It is much more likely that their model is not picking up the effects of some other factor that determines the demand for dairy products. That is, the presumed *ceteris paribus* is not so *paribus*.

A second consideration is that the elasticities derived in AIDS models are elasticities of *quantity*, not of *price* or of *expenditure*. That is, if advertising elasticity is positive and significant, then one can conclude that advertising increases quantity demanded of the advertised product. That is, q_i increases. It is possible for this to occur without any significant increase in price. Profits do not rise if the industry faces constant or rising costs.

Finally, the size of advertising elasticities must not be equated with the size of potential returns for producers (Green, Carman and McManus). Even if the actual advertising elasticity is positive and significant, producer returns depend on factors such as the cost of expanding production to meet higher demand and the cost of the advertising campaign.

Conclusions

Demand systems are dynamic in nature and any attempt to model demand should account for the data's inherent dynamic time-series properties. This article outlines the nature of the demand and supply-side dynamics that can affect the effectiveness of advertising over the short and long-term horizons.

An estimable model is developed to account for the aforementioned dynamics in the form of an error-correction Almost Ideal Demand System. This model is applied to US meat data, and elasticity estimates from the dynamic model are compared to those from a static model. The advertising elasticity estimates from the dynamic, error-correction model seem to perform better than their static counterparts. The results for price elasticities are mixed. There are several reasons, however, to be cautious when using estimated demand elasticities to make policy decisions about advertising programs.

It should be noted that the full appraisal of a commodity advertising program would require more information that can be gleaned from a demand system. Specifically, the estimation of a vector error correction model could provide information about how quickly prices are likely to respond to an advertising-induced price shock. Also, the costs of increasing output to meet higher demand would have to included in any benefit-cost study. However the primary goal of this article is to outline the importance of dynamics when analysing advertising, and to present a method that improves on the current state of the art.

Footnotes

[i] Muth disequilibrium models consist of differential equations, often in demand, that illustrate relationships between changing prices, or other exogenous variables, and demand. See Muth for an exposition of the model.

[ii] The PIGLOG class of cost functions are derived from “price independent generalised linear” budget share equations. Specific selection of functional forms is required for practical application. See Deaton and Muellbauer for a discussion of these forms and the aggregation properties of the PIGLOG cost functions.

[iii] The Johansen test tables have not been included in an effort to conserve space. The tables are available upon request.

[iv] The Johansen procedure was not applied to all 10 variables in the system because of degrees of freedom restriction. However, iterative Engle-Granger cointegration tests were performed on all 10 variables and advertising expenditures were found to be not cointegrated with shares and prices.

Figure 1. Market Force Dynamics

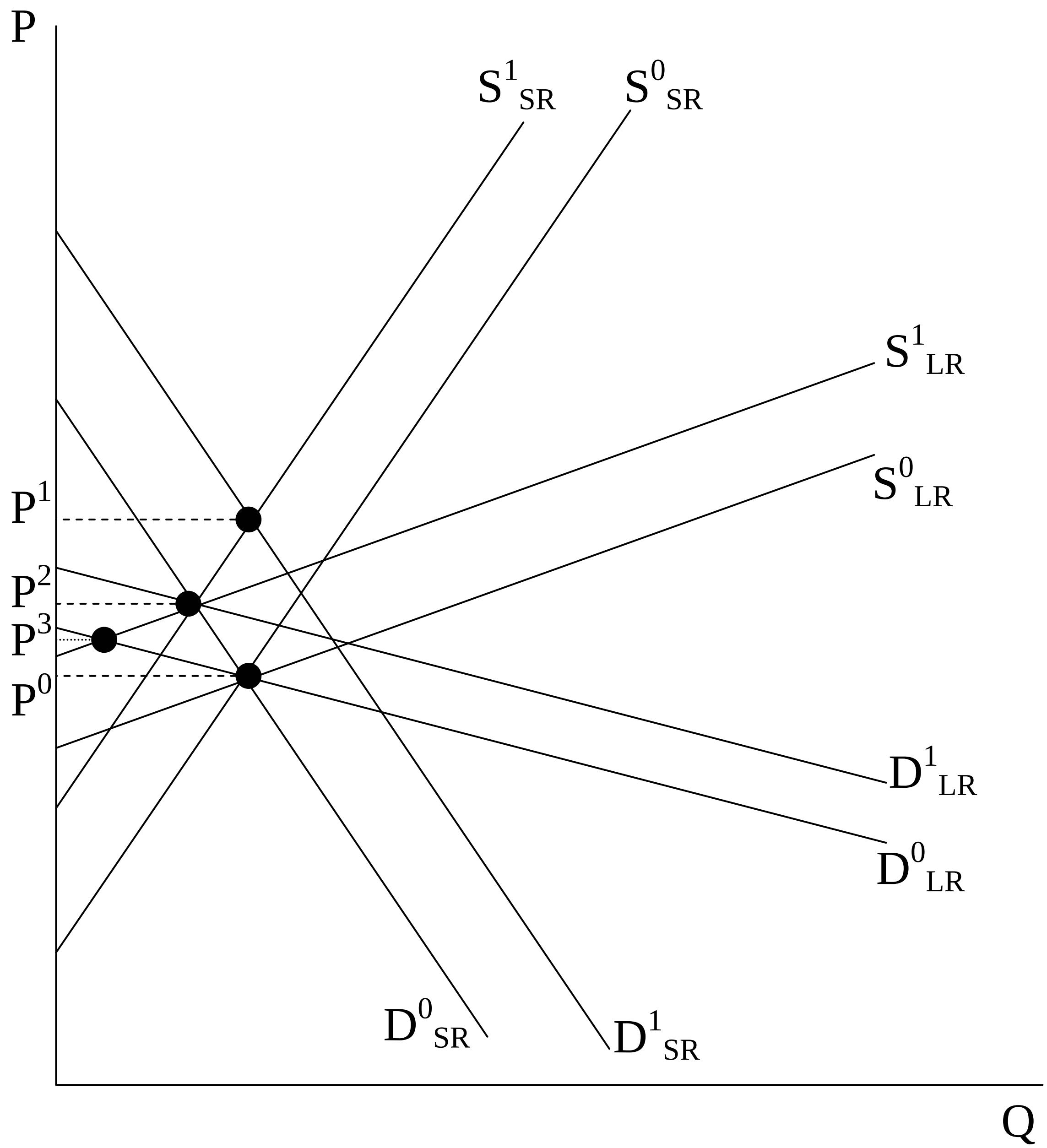

Table 1. Parameter Estimates

	I	I_{EC}		I	I_{EC}
α_b	0.7036	-0.0014	α_f	0.0708	-0.0017
	32.7525	-1.0865		7.8904	-1.2074
π_b		-0.1886	π_f		-0.4084
		-1.7227			-3.5192
γ_{bb}	-0.1566	-0.0276	γ_{fb}	-0.0054	0.0364
γ_{bc}	0.0739	0.0034	γ_{fc}	-0.0001	0.0164
	3.2349	0.3308			
γ_{bf}	-0.0054	0.0364	γ_{ff}	0.0094	-0.0843
	-0.4407	1.8499			
γ_{bp}	0.0881	-0.0123	γ_{fp}	-0.0039	0.0315
	7.9826	-0.8516		-0.4658	1.8983
β_b	0.0083	-0.0177	β_f	0.0177	0.0753
	0.2491	-0.8179		1.2727	2.5932
λ_b		-0.0039	λ_f		0.0072
		-1.3370			2.1974
δ_{bb}	-0.0068	0.0033	δ_{fb}	0.0022	0.0015
	-3.1602	1.8789		2.0594	0.8091
δ_{bp}	-0.0222	-0.0018	δ_{fp}	0.0025	-0.0023
	-5.5181	-0.9089		1.3426	-1.0692
R^2	0.9238	0.1495	R^2	0.6087	0.3620

α_c	0.0488	0.0023	α_p	0.1769	0.0008
	2.3502	2.5492			
π_c		-0.0097	π_p		0.6068
		-0.0767			
γ_{cb}	0.0739	0.0034	γ_{pb}	0.0881	-0.0123
γ_{cc}	-0.0662	-0.0124	γ_{pc}	-0.0076	-0.0075
γ_{cf}	-0.0001	0.0164	γ_{pf}	-0.0039	0.0315
	-0.0098	1.4296			
γ_{cp}	-0.0076	-0.0075	γ_{pp}	-0.0767	-0.0117
	-0.7234	-0.7649			
β_c	0.0253	-0.0277	β_p	-0.0512	-0.0299
	0.8200	-1.8995			
λ_c		-0.0019	λ_p		-0.0015
		-0.9439			
δ_{cb}	0.0098	0.0005	δ_{pb}	-0.0052	-0.0054
	4.9518	0.4614			
δ_{cp}	0.0161	-0.0002	δ_{pp}	0.0036	0.0043
	4.1955	-0.1377			
R^2	0.8911	0.0803			

Table 2. Elasticities

Uncompensated Price Elasticities

Short-run elasticities for Model I

	Beef	Poultry	Fish	Pork
Beef	-0.6002	-0.1796	0.0151	-0.2148
Poultry	-0.2409	-0.7232	0.0081	0.0528
Fish	0.1667	0.0516	-1.1006	0.1032
Pork	-0.4275	-0.0157	-0.0006	-0.7526

Short-run elasticities for I_{EC}

	Beef	Poultry	Fish	Pork
Beef	-0.9492	-0.0200	-0.0948	0.0192
Poultry	-0.0568	-0.9797	-0.0727	0.0011
Fish	-0.0717	0.0371	0.1448	-0.1501
Pork	0.0003	-0.0008	-0.1316	-0.9848

Long-run elasticities for I_{EC}

	Beef	Poultry	Fish	Pork
Beef	-0.7985	-0.0168	-0.0798	0.0162
Poultry	-0.0562	-0.9703	-0.0720	0.0011
Fish	-0.0509	0.0263	0.1028	-0.1066
Pork	0.0009	-0.0022	-0.3346	-2.5045

Advertising Elasticities

Short-run elasticities for Model I

	Beef	Pork
Beef	-0.0169	-0.0550
Poultry	0.0387	0.0637
Fish	0.0293	0.0362
Pork	-0.0217	0.0100

Short-run elasticities for I_{EC}

	Beef	Pork
Beef	0.0083	-0.0045
Poultry	0.0022	-0.0008
Fish	0.0186	-0.0285
Pork	-0.0207	0.0165

Long-run elasticities for I_{EC}

	Beef	Pork
Beef	0.0070	-0.0038
Poultry	0.0022	-0.0008
Fish	0.0132	-0.0203
Pork	-0.0527	0.0420

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