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Meat - Demand

A Globally Flexible Model of the Effects of Generic Advertising of Beef and Pork on U.S. Meat Demand

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Abstract

Specification error resulting from the choice of an incorrect functional form can lead to biased estimates. A new, more flexible and more general demand system is derived in this paper, and applied to evaluate the effects of functional form choices on the estimated effects of beef and pork advertising on the demand for meat in the United States.

The new demand system, the Nested PIGLOG (NEP) model, combines three types of generalizations used previously in the literature: (1) the inclusion of pre-committed quantities (analogous to the Linear Expenditure System (LES) generalization of the Cobb-Douglas model), (2) nesting the Almost Ideal (AI) and Translog (TL) models together (Lewbel 1989), and (3) using the Fourier flexible functional form to augment other functional forms (Chalfant 1987). In particular, the new demand system augments the expenditure function of the Generalized Almost Ideal Translog (GAITL) model (Bollino and Violi 1990) with the expenditure function for the Fourier flexible functional form (Gallant 1981, 1982).

The NEP model nests all of the previously existing demand systems that are consistent with PIGLOG preferences, and five new models. In this paper, we estimate the NEP demand system including advertising variables, using U.S. meat consumption data, and test the appropriateness of the sets of parametric restrictions in the NEP model that define its nested special cases. We also test the statistical (and economic) significance of advertising effects, given each of the functional form restrictions.

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In the United States, agricultural producer groups spend almost $1 billion per year on generic promotion programs, funded using mandated assessments. The controversial nature of the programs, combined with their economic importance, has led to a growing interest in evaluating their effects. A first step in any such evaluation is to establish the statistical and economic significance of the demand response to advertising.

Previous studies have shown that the choice of functional form for demand equations can have important effects on hypothesis tests and measures of demand response to price or advertising. It is desirable to choose a demand system that will do a good job of approximating the true (but unknown) functional form without involving too many parameters; a flexible, but parsimonious, model is desired. In addition, the chosen demand system should be integrable (i.e., consistent with consumer theory). In this paper, we derive a new demand system that meets these requirements, the Nested PIGLOG (NEP) model. This demand system is more general than previously existing demand systems, and nests a total of thirteen demand systems as special cases.

The NEP model is used to test whether advertising by the Beef Industry Council (BIC) and the National Pork Producers' Council (NPPC) had statistically significant effects on the per capita demands for beef, pork, and poultry in the United States. Each alternative functional form is estimated with and without advertising, and the resulting estimates are compared and evaluated.

Deriving the Nested PIGLOG (NEP) model

The NEP model combines the expenditure function of the Generalized Almost Ideal Translog (GAITL) model (Bollino and Violi 1990) with the expenditure function for the Fourier flexible functional form (Gallant 1981, 1982), and nests all of the known demand systems that are consistent with PIGLOG (Price-Independent Generalized Logarithmic) preferences: the LES, AI, TL (exactly aggregable), Generalized Almost Ideal (GAI), Almost Ideal Translog (AITL), Generalized Translog (GTL), GFAI, and GAITL models. In addition, the NEP model nests five new models: the Globally Flexible Linear Expenditure System (GFLES), the Globally Flexible Translog (GFTL) model, the Globally Flexible Generalized Almost Ideal (GFGAI) model, the Globally Flexible Almost Ideal Translog (GFAITL) model, and the Globally Flexible Generalized Translog (GFGTL) model. Models of the PIGLOG class predominate in modern demand analysis for various theoretical and practical reasons.

The NEP model can be derived using an expenditure function of the form

$$\mathrm{E}(\mathrm{p}, u) = \mathrm{p}'\mathrm{c} + \exp\left\{ \frac{\delta + \alpha'\hat{\mathrm{p}} + \frac{1}{2}\hat{\mathrm{p}}'\Gamma\hat{\mathrm{p}} + 2\sum_{\alpha=1}^{A}\left\{u_\alpha \cos\left(\lambda \mathrm{k}_\alpha'\hat{\mathrm{p}}\right) - v_\alpha \sin\left(\lambda \mathrm{k}_\alpha'\hat{\mathrm{p}}\right)\right\} + u\beta_0 \prod_{k=1}^{N} p_k^{\beta_k}}{\alpha'\iota + \hat{\mathrm{p}}'\Gamma\iota} \right\}$$

where E is the minimum expenditure to achieve utility u, given an N-vector of prices, p, an N-vector of logarithms of prices, $\hat{\mathrm{p}}$, an N-vector of ones, ι, a multi-index, k_α, and a scaling factor, λ. The parameters to be estimated are the scalars δ, u_α, and v_α, the N-vectors c, α, and β, and the $N\times N$ matrix Γ, and the following restrictions are assumed to hold:

$$\iota'\Gamma\iota = 0,\ \Gamma = \Gamma',\ \alpha'\iota = 1,\ \mathrm{k}_\alpha'\iota = 0 \text{ and } \beta'\iota = 0.$$

Expenditure share equations for the NEP model are of the form

$$\mathrm{s} = \left(\frac{1}{M}\right)\phi + \frac{M^*}{M}\left\{ \frac{\alpha + \Gamma\pi^* + \beta\left[\mathrm{d}(\hat{\mathrm{p}})\ln M^* - \ln \widetilde{P}\right] - 2\lambda\sum_{\alpha=1}^{A}\left\{u_\alpha \sin\left(\lambda \mathrm{k}_\alpha'\hat{\mathrm{p}}\right) + v_\alpha \cos\left(\lambda \mathrm{k}_\alpha'\hat{\mathrm{p}}\right)\right\}\mathrm{k}_\alpha}{\mathrm{d}(\hat{\mathrm{p}})} \right\}$$

where

$$\mathrm{d}(\hat{\mathrm{p}}) = \alpha'\iota + \hat{\mathrm{p}}'\Gamma\iota.$$

$\phi = p'c$ denotes expenditures on pre-committed quantities (c), M denotes total expenditure on the group of goods, $M^* = M - p'c = M - \phi$ denotes supernumerary expenditures, and

$$\ln \widetilde{P} = \delta + \alpha'\hat{p} + \tfrac{1}{2}\hat{p}'\Gamma\hat{p} + 2\sum_{\alpha=1}^{A}\{u_\alpha \cos(\lambda k'_\alpha \hat{p}) - v_\alpha \sin(\lambda k'_\alpha \hat{p})\}.$$

Figure 1 depicts the linkages among the nested models and Table 1 summarizes the various parametric restrictions that yield the demand systems nested within the NEP model. Among these models, only those that include demand shift variables (time trends, seasonal effects, or advertising) as modifications of the pre-committed quantity parameters are fully consistent with theory, flexible, and parsimonious. This is important because studies using these types of models with time-series data on food consumption have typically found statistically significant trends, seasonality (if quarterly data are used), and other shifters. Piggott (1997) showed that the models without pre-committed quantities cannot simultaneously be made consistent with demand theory and incorporate shifters, as discussed below.

The six models that did not include pre-committed quantity parameters (the AI, TL, AITL, GFAI, GFTL, and GFAITL) include the models that have been most popular in food demand studies, especially the AI. In the AI model, it has been common practice to include advertising and any other "shift" variables (including time trends and seasonal dummies) as intercept shifters in the share equations. Unfortunately, this procedure (or the equivalent treatment in any of the six models) gives rise to estimates of economic effects, including price and advertising elasticities, that are not invariant with respect to the units in which quantities (and prices) are measured. The invariance problem has not been recognized previously, perhaps because most studies have used a linear approximation to the AI model which, incidentally, avoids the problem.[1] Another option might be to make all of the parameters, not just the intercepts, depend on advertising, but this option is usually too demanding of degrees of freedom; it contradicts our desire for parsimony.

[1] Although this avoids the problems mentioned above, other problems arise when making this substitution. Stone's price index itself is not invariant to disproportionate changes in units of measurement (see Moschini (1995) for a detailed discussion of this point); in addition, the AI model is not integrable when estimated with Stone's price index instead of the true price index.

Alternative ways of including advertising in the NEP class of models, including the six cases without pre-committed quantity parameters, give rise to different problems. For example, in a scaling approach, in which "effective" prices and quantities depend on advertising and actual prices and quantities, advertising that increases demand will lower the effective price when demand is elastic, and will increase the effective price when demand is inelastic, so that the consequences for consumer welfare switch sign when demand changes from elastic to inelastic; the model is inflexible (Alston, Chalfant, and Piggott 1997). The inclusion of advertising variables as modifiers of pre-committed quantity parameters is the only way we have identified, so far, that is parsimonious, flexible, and yields estimates that are invariant with respect to quantity units.

Data

The analysis uses quarterly data from 1979 to mid-1995 on prices, consumption, and expenditure on three goods (beef, pork, and poultry) based on preliminary analysis which suggested that meat could be treated as a weakly separable group, and that chicken and turkey could be aggregated. The quantities are measured in pounds (retail weight) per capita of domestic disappearance, and the prices are in retail cents per pound, as documented in detail by Piggott (1997). The expenditure variable in the model is the sum of the expenditures across the three meat categories. The advertising data measure expenditure by the Beef Industry Council (BIC) and the National Pork Producers' Council (NPPC) in thousands of dollars per quarter (similar to those used by Brester and Schroeder 1995). Further details on these data, and data on population and the deflators used, can be found in Piggott (1997).

Econometric Results

Demand shift variables (quadratic time trends and seasonal dummies) were always statistically significant in the eight models that include pre-committed quantities, whether the models were estimated with and without advertising. Advertising effects often persist over time. It was determined econometrically that the effects of BIC and NPPC advertising lasted four quarters after the initial quarter. Advertising by the BIC and NPPC over the period 1979(1)-1995(2) jointly had statistically significant effects on the demands for beef, pork, and poultry. This finding was consistent across the eight models. In the nested hypothesis tests, only two of the models, both of which are new—the GFGAI and GFGTL models—were not rejected in favor of the new and most general functional form, the NEP model (see Table 2). Choosing a preferred model from these three new functional forms was difficult, since the economic effects implied by the estimates were remarkably similar among these three models (see Table 3). Interestingly, the choice of functional form had no effect on the finding that advertising by the BIC and NPPC had statistically significant effects on the demands for beef, pork, and poultry.

As can be seen in table 3, many of the elasticities are very similar across the eight models, but there is some variation and it may be important in some cases. The entries in table 3 are the means of elasticities computed at every data point in the sample. For most of the price and income elasticities, important differences among models are not found until the relatively restrictive LES (or GFLES) form is used; these forms were rejected.

In table 3, $\omega_{i,k}$ is the elasticity of demand for good i with respect to advertising of type k. For instance, it can be seen that, across models, the (mean) estimated elasticity of demand for beef with respect to BIC advertising ranges from 0.015 in the NEP to -0.005 in the LES (-0.004 in the GFLES). The more-flexible models tended to yield larger (more positive) own-advertising elasticities of demand for beef. Adding-up restrictions meant that the cross-commodity effects of beef advertising became more negative (i.e., either larger negative effects or switched from positive to negative) when the model specification led to a larger own-commodity effect of beef advertising. For pork, however, the own advertising elasticities were very similar across all of the models apart from the LES and GFLES (ranging from 0.033 to 0.042 in the other six models), and so were the cross-commodity advertising elasticities, for the most part.

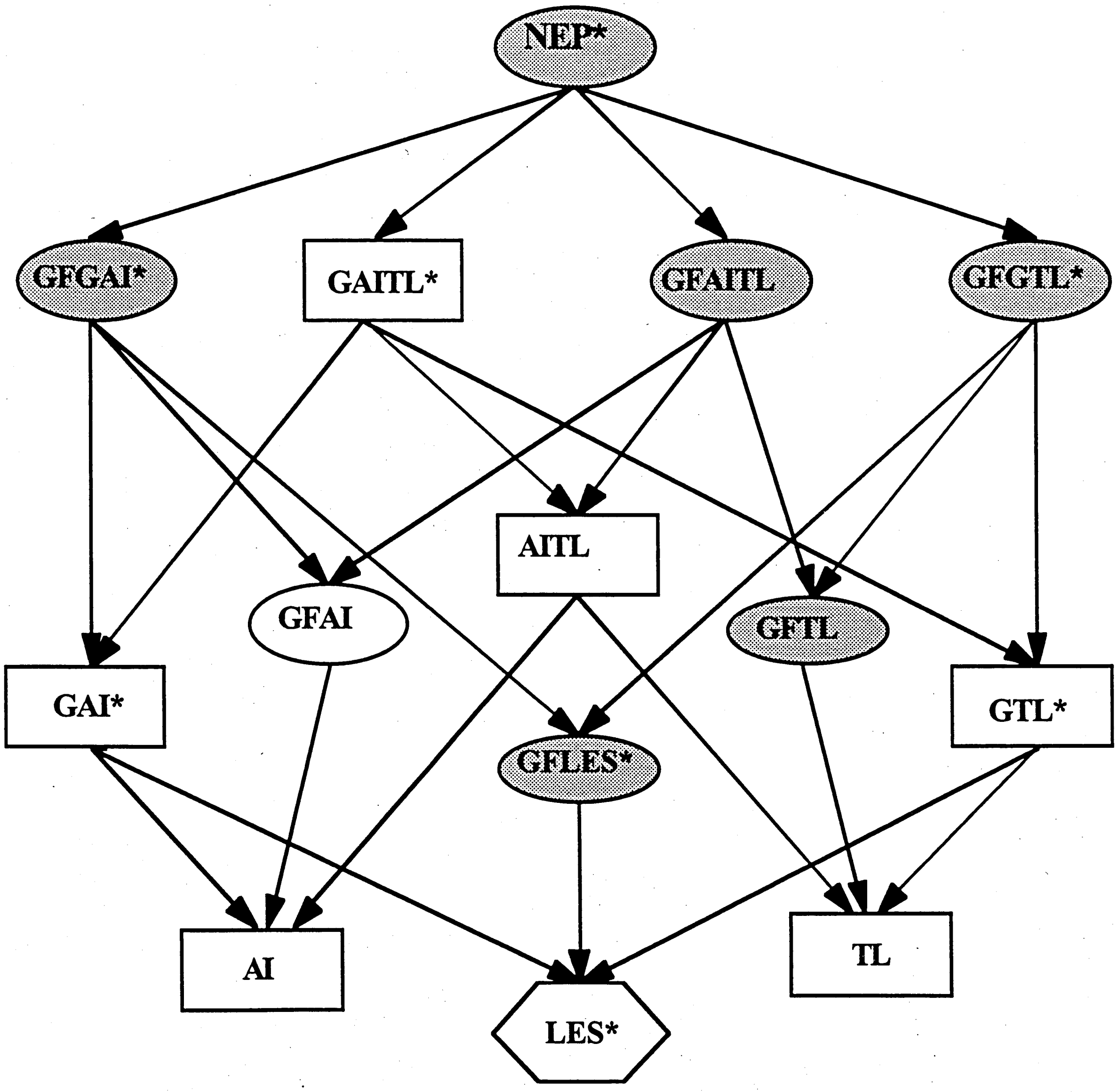
These results mean that the choice of a particular functional form for demands, even restricting attention to the NEP class, could have very profound implications for the estimated elasticities of demand response to advertising. Compared with the other forms, the LES (or the LES augmented with Fourier terms, the GFLES) implies much larger own- and cross-commodity effects of pork advertising and much smaller own- and cross-commodity effects of beef advertising (indeed, opposite signs on the own-commodity effect on beef and the cross-commodity effect on poultry). Both the LES and GFLES were rejected statistically in favor of the models that nest them, so these estimates can be discounted somewhat—but this does not weaken the point that this model illustrates: an arbitrary choice of a single model could lead to fragile, or seriously wrong, estimates. Among the remaining models, there is little difference in relation to the measured effects of pork advertising, but the beef advertising effects increase when (a) models of the AI or TL form are nested together, (b) models of either the AI or TL form are augmented with Fourier series, or (c) both of these generalizations are used. As a result, the own-commodity effect of beef advertising could be represented by an elasticity as small as 0.004 (the GTL) or as large as 0.015 (the NEP). In each of the three models that were not statistically rejected (the GFGAI, the GFTL, and the NEP), this elasticity was about twice as large as in the models that were rejected (the GAITL, the GAI, and the GTL).

Conclusion

In this paper, we have described the NEP model, in which advertising and other shifters can be incorporated as modifiers of pre-committed quantity parameters, which preserves the desirable characteristics of the model and allows advertising effects to be measured flexibly and parsimoniously. The illustrative application to measuring demand response to U.S. beef and pork advertising indicates that the advertising and other demand shift variables belong in the model, regardless of the other aspects of the specification. This application highlights some key issues that are of a more general nature, while providing estimates that are intrinsically interesting as well.

The NEP model is a useful generalization of popular demand systems, which can be used to evaluate various alternatives as special cases. With greater flexibility and generality comes some greater demands for data and greater difficulty of estimation, which might not be justified by the probable benefits for some problems, given the nature of typically available data. Until the model has been applied and tried with other data sets, this benefit-cost question is a matter for speculation. Studies that use only a single functional form and do not evaluate its implications might suffer from fragility (Leamer 1983; Alston and Chalfant 1991). In our application, we saw small effects on the estimates of price and expenditure elasticities, and the elasticities of demand with respect to pork advertising, once we had gone beyond the least-flexible models in the class. However, the beef advertising elasticities were much more sensitive to functional form choices, even among the relatively flexible models, only some of which were statistically rejected. The elasticities in the models that were not rejected are in the range to suggest that the economic effects of advertising on demand are likely to have been economically as well as statistically important and worthy of further investigation.

Figure 1: The Nested PIGLOG (NEP) model



* Model includes pre-committed quantities
Previously existing demand system
New demand system
Globally flexible functional form
Locally flexible functional form
Indicates a nested model

Table 1: The Different Models Nested within the Nested PIGLOG Demand System

Model	Restrictions			
	$c_i=0\ \forall i$	$\Gamma\iota=0$	$\beta=0$	$v_\alpha=0\ \forall\alpha$ $u_\alpha=0\ \forall\alpha$
Globally Flexible Functional Forms				
Nested PIGLOG (NEP)				
Globally Flexible Generalized Almost Ideal (GFGAI)		x		
Globally Flexible Generalized Translog (GFGTL)			x	
Globally Flexible Almost Ideal Translog (GFAITL)	x			
Globally Flexible Almost Ideal (GFAI)	x	x		
Globally Flexible Translog (GFTL)	x		x	
Globally Flexible Linear Expenditure System (GFLES)		x	x	
Locally Flexible Functional Forms				
Generalized Almost Ideal Translog (GAITL)				x
Generalized Almost Ideal (GAI)		x		x
Generalized Translog (GTL)			x	x
Almost Ideal Translog (AITL)	x			x
Almost Ideal (AI)	x	x		x
Translog (TL)	x		x	x
Non-Flexible Functional Forms				
Linear Expenditure System(LES)		x	x	x

Notes: An x indicates that the restriction is required

Table 2: Log-Likelihood Values and Likelihood-Ratio Tests for Models with Time Trends and Seasonal Dummy Variables and Advertising

	NEP	GFGAI	GAITL	GFGTL	GAI	GTL	GFLES	LES
NEP	615.037							
GFGAI	2.286	613.894						
	(2)							
GAITL	14.766*		607.654					
	(6)							
GFGTL	4.138			612.969				
	(3)							
GAI	15.455*	13.169*	0.689		607.310			
	(8)	(6)	(2)					
GTL	35.962*		21.196*	31.825*		597.056		
	(9)		(3)	(6)				
GFLES	67.578*	65.292*		63.440*			581.249	
	(8)	(6)		(5)				
LES	84.654*	82.368*	69.888*	80.516*	69.199*	48.692*	17.076	572.710
	(14)	(12)	(8)	(11)	(6)	(7)	(12)	

Notes: Diagonal elements are the log-likelihood values for each model. Off-diagonal elements and figures in parentheses are the test statistics and number of restrictions between the more general model and the nested model, respectively. * denotes a test statistic that is significant at the 5% level.

Table 3: Estimated Elasticities for Models With Time Trends and Seasonal Dummy Variables and Advertising (Means).

	NEP	GFGAI	GAITL	GFGTL	GAI	GTL	GFLES	LES
η_{11}	-0.966	-0.956	-0.955	-0.974	-0.950	-0.883	-0.751	-0.792
η_{12}	-0.138	-0.121	-0.122	-0.129	-0.127	-0.127	-0.227	-0.215
η_{13}	-0.160	-0.143	-0.147	-0.148	-0.149	-0.146	-0.210	-0.215
η_{21}	-0.151	-0.146	-0.095	-0.139	-0.095	-0.177	-0.528	-0.375
η_{22}	-0.740	-0.742	-0.703	-0.735	-0.694	-0.673	-0.622	-0.588
η_{23}	-0.179	-0.188	-0.179	-0.188	-0.170	-0.192	-0.222	-0.201
η_{31}	0.203	0.171	0.114	0.204	0.099	0.025	0.110	-0.025
η_{32}	0.006	-0.033	-0.079	-0.018	-0.077	-0.103	0.070	-0.013
η_{33}	-0.252	-0.273	-0.268	-0.258	-0.273	-0.238	-0.049	-0.048
η_{1M}	1.264	1.221	1.224	1.251	1.226	1.156	1.188	1.223
η_{2M}	1.071	1.076	0.977	1.062	0.959	1.042	1.372	1.165
η_{3M}	0.044	0.134	0.233	0.072	0.250	0.317	-0.131	0.086
v_{11}	-0.274	-0.285	-0.280	-0.287	-0.274	-0.244	-0.103	-0.126
v_{12}	0.208	0.213	0.213	0.213	0.209	0.189	0.099	0.120
v_{13}	0.065	0.072	0.067	0.074	0.065	0.055	0.004	0.006
v_{21}	0.434	0.441	0.438	0.441	0.430	0.394	0.225	0.264
v_{22}	-0.447	-0.447	-0.435	-0.444	-0.432	-0.388	-0.247	-0.270
v_{23}	0.013	0.006	-0.003	0.004	0.002	-0.006	0.022	0.006
v_{31}	0.219	0.233	0.223	0.233	0.217	0.176	0.037	0.022
v_{32}	0.019	0.006	-0.013	0.003	-0.005	-0.014	0.034	0.011
v_{33}	-0.238	-0.239	-0.210	-0.236	-0.212	-0.162	-0.071	-0.033
$\omega_{1,BIC}$	0.015	0.010	0.006	0.012	0.004	0.005	-0.004	-0.005
$\omega_{2,BIC}$	-0.007	-0.007	-0.003	-0.008	-0.001	-0.001	-0.006	-0.007
$\omega_{3,BIC}$	-0.028	-0.016	-0.010	-0.018	-0.009	-0.011	0.019	0.023
$\omega_{1,NPPC}$	-0.022	-0.022	-0.021	-0.021	-0.022	-0.023	-0.055	-0.051
$\omega_{2,NPPC}$	0.033	0.037	0.033	0.036	0.034	0.042	0.081	0.075
$\omega_{3,NPPC}$	0.012	0.008	0.010	0.008	0.011	0.003	0.033	0.029
NSD	80.33	83.33	93.94	86.36	96.97	100.00	53.03	80.30

Notes: Notes: η_{ij} and v_{ij} are the Marshallian and Hicksian price elasticities of demand for the i^{th} good with respect to the j^{th} price, and η_{iM} is the expenditure elasticity of demand for the i^{th} good, where i=1 for beef, 2 for pork, and 3 for poultry. $\omega_{i,k}$ is the elasticity of demand for the i^{th} good with respect to the k^{th} type of advertising. *NSD* is the percentage of observations that satisfy the curvature requirements of negative semi-definiteness of the Slutsky matrix.

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