The Nested PIGLOG Model: An Application to U.S. Food Demand

Nicholas E. Piggott

A new demand system is introduced, the Nested PIGLOG model, nesting thirteen other demand systems including five that are also new. This new model and its nested special cases are applied to models of U.S. food demand that include food-at-home (FAH), food-away-from-home (FAFH), and alcoholic beverages. Although nested tests and out-of-sample forecasting performance favor generalizing models to a certain degree, statistically insignificant improvements to in-sample-fit and even poorer out-of-sample forecast accuracy undermine further generalizations. Based on a subset of preferred models, FAFH is found to be price and income elastic compared to FAH which is price and income inelastic.

Key words: demand systems, forecast errors, nested tests, U.S. food demand.

Researchers using econometric models to analyze consumer demand must decide what parametric form to assign to a particular demand function. Theory gives little guidance about what these parametric forms should be, but specification choices can affect results; hence results are conditioned on a particular choice of a parametric form. Typically, functional forms are chosen that are both convenient to estimate and are thought to have desirable approximation properties. Flexible functional forms are considered to have such desirable properties and can reduce the specification bias caused by the selection of an incorrect functional form.

Over the past several decades, increasingly more general flexible functional forms have been introduced on the grounds that more general models may yield better approximations to underlying preferences. The purpose of this article is to introduce a demand system combining several previously adopted generalizations within a single demand system, resulting in a demand system consisting of thirteen other demand systems, five of which are also new. The nested structure facilitates a comparison of competing functional forms using conventional hypothesis tests and shows how elasticities are affected by generalizing models. Furthermore, because all of the nested models have the same dependent variable, a comparison can be made of out-of-sample forecast accuracy as a criterion for model selection.

The remainder of the article proceeds as follows. The next section includes a brief outline of the development of more general functional forms in demand analysis. This is followed by the introduction of the new functional form and an application to U.S. food demand. Model comparisons using in-sample criteria, such as nested tests and comparisons of estimated elasticities are undertaken. In the final section, several out-of-sample forecasting criteria are developed and employed to further evaluate generalizing demand models.

Development of More General Functional Forms in Demand Analysis

Much attention in demand analysis has focused on demand systems that are consistent with the logarithmic subclass of price-independent generalized linear (PIGL) preferences, which Muellbauer called PIGLOG. This class of preferences has the desirable property of permitting exact aggregation over consumers (Muellbauer). PIGLOG preferences can be expressed by an expenditure function of the form $\ln E(p, u) = a(p) + u \cdot b(p)$, where $E(p, u)$ is the minimum expenditure necessary to attain a specific level of utility, u, for a given N-vector of prices, p. The functions $a(p)$ and

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$b(p)$ are assumed to be positive and linearly homogeneous in prices. Demand equations can be derived directly from an application of the logarithmic form of Shepard's lemma, yielding the vector of Hicksian share equations, $s^H(p, u)$. Because the relationship between the logarithm of expenditures and utility is linear, the unobservable Hicksian share equations can be converted to the observable Marshallian demand functions.

The PIGLOG class of preferences includes some of the most commonly estimated locally flexible functional forms such as the almost ideal (AI) demand model (Deaton and Muellbauer) and the exactly aggregable translog (TL) model (Christensen, Jorgenson, and Lau).[1] Several alternative generalizations of the these two models have been developed including versions incorporating the so-called "pre-committed quantities."[2] The expenditure function used to characterize this generalization allows for a portion of total expenditures (M) to be allocated to these pre-committed quantities. The amount of expenditure remaining after the pre-committed quantities have been bought, is referred to as supernumerary expenditure (M^*), defined as $M^* = M - p'c$, where c is the N-vector of pre-committed quantities. An expenditure function allowing for pre-committed quantities can be written as $E(p, u) = p'c + E^*(p, u)$, where $E^*(p, u)$ is the expenditure function for supernumerary expenditures. For $E(p, u)$ to nest models consistent with PIGLOG preferences, this transformed expenditure function must be of the form $E(p, u) = p'c + \exp[a(p) + u \cdot b(p)]$. The functional form of alternative demand systems varies according to the forms assigned to $a(p)$ and $b(p)$. The simplest, the LES model, is derived by specifying the supernumerary expenditure function to be of the Cobb-Douglas form (i.e., $a(p) = \alpha_0 + \alpha'\hat{p}$ and $b(p) = 1$, where $\hat{p}$ is the N-vector of logarithm of prices). More general forms include the generalized translog (GTL) model (Pollak and Wales) and the generalized almost ideal (GAI) model (Bollino), derived by assigning supernumerary expenditures to be of the TL and AI forms, respectively. An alternative way of generalizing the TL and AI models is to nest them into a composite model to form what will be referred to as the almost ideal translog (AITL) model (Lewbel). Bollino and Violi then included pre-committed quantities in the AITL model to develop the generalized almost ideal translog (GAITL) model.

Locally flexible functional forms, such as the GAITL model, arguably represent an improvement over functional forms that restrict elasticities before estimation such as the Cobb-Douglas model. Nonetheless, the development of locally flexible functional forms has failed to put to rest the problem of potential specification error resulting from the use of an incorrect functional form. A locally flexible functional form does not avoid specification errors unless it is, in fact, the true model. White demonstrates this point with a simple diagram. No useful statistical properties are apparent from the definition of local flexibility (Gallant 1981). An appropriate measure of approximation error needs to determine the values of parameters in the approximating function in such a way that both the prediction errors of the underlying function, and the errors with which derivatives are measured, are all made small over the entire range of the data (globally) rather that just at a particular point (locally). Gallant's (1981, 1982, 1984) work in developing the concept of global flexibility and Diewert's criterion of local flexibility both have the same objective: to make the distance between the approximating function and the true underlying function small, as well as the distance between their respective derivatives. One definition is local and the other global, however, and the measures of distance are therefore not the same. Gallant (1981) noted that the Sobolev norm is the appropriate measure of distance for approximating unknown functional forms because this measure of distance appropriately takes into account errors in the approximation throughout the domain of the function, as well as taking into account the errors in approximating derivatives.[3] Gallant's work in finding the Fourier series approximations applicable to estimating factor demands and consumer demands, means that these demands may have the desirable property that specification bias can be made asymptotically negligible.

[1] Locally flexible functional forms are thought to provide a local, second-order approximation to an arbitrary function at some point in the price and income space. The definition of a second-order approximation provided by Diewert, identifies the minimum number of parameters needed so that, in theory, the value of the underlying true expenditure function and the approximating function, as well as equations for their respective first and second derivatives, can be equated at a particular point in the parameter space.

[2] The terms *subsistence* or *necessary* quantities have also been used previously.

[3] For the technical details and definitions of the Sobolev norm, and theorems linking the Fourier series to the Sobolev norm, see Gallant (1981).

Thus, an alternative set of generalizations is available involving the use of Fourier flexible forms. These generalizations may be used instead of, or combined with, the generalizations involving nesting the AI and TL models or incorporating pre-committed quantities. Chalfant nested part of the AI model's expenditure function within a Fourier flexible form, to develop the globally flexible almost ideal (GFAI) model.[4] Nesting locally flexible functional forms within Fourier flexible forms is motivated by the theoretical advantages of the Fourier flexible form, and by some encouraging simulation results in Chalfant and Gallant.

$$(1)\quad E(p,u) = p'c + \exp\left[\frac{\delta + \alpha'\hat{p} + (1/2)\hat{p}\Gamma\hat{p} + 2\sum_{a=1}^{A}\{u_a\cos(\lambda k_a'\hat{p}) - v_a\sin(\lambda k_a'\hat{p})\} + u\beta_0\prod_{k=1}^{N} p_k^{\beta_k}}{\alpha'\iota + \hat{p}'\Gamma\iota}\right]$$

$$(2)\quad s = \left(\frac{1}{M}\right)\phi + \left(\frac{M^*}{M}\right)\left[\frac{\alpha + \Gamma\pi^* + \beta[d(p)\ln M^* - \ln\tilde{P}] - 2\lambda\sum_{a=1}^{A}\{u_a\sin(\lambda k_a'\hat{p}) + v_a\cos(\lambda k_a'\hat{p})\}k_a}{d(p)}\right]$$

The Nested PIGLOG model

The demand system developed in this article combines all three types of generalizations used previously in the literature—pre-committed quantities, nesting the AI and TL models, and combining locally flexible models within Fourier flexible functional form. In particular, this demand system nests the expenditure function of the GAITL model within the expenditure function for the Fourier flexible functional form. The new demand system is given the name the nested PIGLOG (NEP) model, since it nests demand systems that are consistent with PIGLOG preferences for supernumerary expenditures or total expenditures if pre-committed quantities are not permitted.

The NEP demand system is derived from an expenditure function of the form (1), where $\hat{p}$ is an N-vector of logarithms of prices, ι is an N-vector of ones, k_a is a multi-index (a vector with integer components),[5] λ is a scaling factor,[6] and A is the number of included multi-indexes. The parameters to be estimated are the scalars δ, u_a, v_a, the N-vectors c, α, and β, and the $N \times N$ matrix Γ. $E(p,u)$ is linearly homogeneous in prices if the following restrictions hold: $\iota'\Gamma\iota = 0$, $\Gamma = \Gamma'$, $\alpha'\iota = 1$, $k_a'\iota = 0$, and $\beta'\iota = 0$.

Share equations for the NEP model are of the form (2), where

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

$$\pi^* = \ln\left[\left(\frac{1}{M^*}\right)p\right]$$

$$\ln\tilde{P} = \delta + \alpha'\hat{p} + (1/2)\hat{p}\Gamma\hat{p} + 2\sum_{a=1}^{A}\{u_a\cos(\lambda k_a'\hat{p}) - v_a\sin(\lambda k_a'\hat{p})\},$$

and s is the N-vector of budget shares, M is total expenditure, and ϕ is the N-vector of pre-committed expenditures (i.e., $\phi_i = p_i c_i$). Provided that the restrictions mentioned above are satisfied, (2) represents a system of demand equations satisfying adding-up and are

[4] Wohlgenant combined the Fourier flexible form with the linear expenditure system to develop the Fourier linear expenditure system (FLES) model. The way in which the Fourier flexible form was included in the FLES model is different from the generalization proposed here to form the GFLES model described later. Although the models are different, both nest the LES model as a special case.

[5] Multi-indexes are vectors of length N that reduce the notational complexity of multivariate Fourier series expansions (see Gallant (1982) for details).

[6] Because a Fourier series involves a periodic function in each of the arguments the scaling of the data is important. The scaling factor λ ensures that the data fall within the $(0, 2\pi)$ interval (see Gallant (1981) for details).

Table 1. The Different Models Nested Within the Nested PIGLOG Demand System

	Restrictions			
Model	$c_i = 0 \; \forall \; i$	$\Gamma\iota = 0$	$\beta = 0$	$v_a = 0 \; \forall \; a$ $u_a = 0 \; \forall \; a$
Globally Flexible Functional Forms				
Nested PIGLOG (NEP)				
Globally flexible generalized almost ideal (GFGAI)		×		
Globally flexible generalized translog (GFGTL)			×	
Globally flexible almost ideal translog (GFAITL)	×			
Globally flexible almost ideal (GFAI)	×	×		
Globally flexible translog (GFTL)	×		×	
Globally flexible linear expenditure system (GFLES)		×	×	
Locally Flexible Functional Forms				
Generalized almost ideal translog (GAITL)				×
Generalized almost ideal (GAI)		×		×
Generalized translog (GTL)			×	×
Almost ideal translog (AITL)	×			×
Almost ideal (AI)	×	×		×
Translog (TL)	×		×	×
Non-Flexible Functional Forms				
Linear expenditure system (LES)		×	×	×

Note: The × indicates that the restriction is required.

homogeneous to degree zero in prices and expenditure.

The NEP demand system nests the GFAI model, the GAITL model, and each of the locally flexible forms nested in the GAITL model, as well as five new demand systems: the globally flexible generalized almost ideal (GFGAI) model, the globally flexible almost ideal translog (GFAITL) model, the globally flexible generalized translog (GFGTL) model, the globally flexible translog (GFTL) model, and the globally flexible linear expenditure system (GFLES) model.[7] Table 1 provides the various parametric restrictions that yield the demand systems nested within the NEP model and figure 1 depicts the linkages among them.

An Application to U.S. Food Demand

In this section, the NEP model is applied to aggregate annual time-series data of food demand in the United States over the period 1968–99. Expenditures on food are maintained to be weakly separable from expenditure on all other goods. Annual consumer expenditure data on food-away-from-home (FAFH), food-at-home (FAH), and alcoholic beverages are from the United States Department of Agriculture. The price indexes used for each category are from the Bureau of Labor Statistics. Per capita consumption series are constructed by dividing the expenditure data by the appropriate price index and by U.S. population data from the Bureau of Census.

Food expenditure has been a declining component of personal disposable income, its share declined from 19% in 1968 to 13% in 1999. Over the same period, the FAFH share has been stable at around 6%, whereas the FAH and alcoholic beverage share of 10.8 and 2.7% has shrunk to 6.2 and 1.4%, respectively. If these trends continue, expenditure on FAFH will soon account for the largest component of the U.S. consumer's food budget. There is an abundant literature investigating the factors responsible for these changes and the increased importance of FAFH.[8] Factors that have been investigated include changes in household demographics, female participation in the work force, increased availability of FAFH, changes in income distribution, certain meal types, the value of time, different facilities types, and geographical location. This literature has utilized cross-sectional data such

[7] The expenditure functions and the resulting share equations for these new demand models are shown in detail in Piggott.

[8] See, for example, studies by Prochaska and Schrimper; Senauer; Kinsey; Lee and Brown; McCracken and Brandt; Yen; Jensen and Yen; Park et al.; Nayga; Byrne, Capps, and Saha; and Park and Capps.

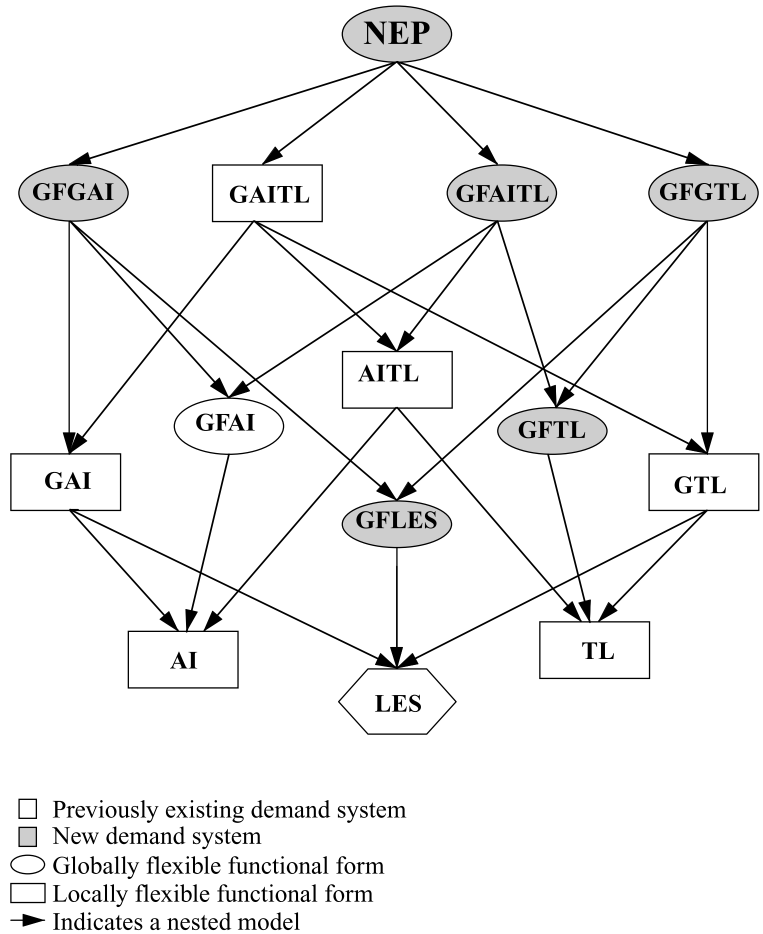

Figure 1. The nested PIGLOG (NEP) model

as panel or diary data from household surveys and in some instances these surveys are repeated providing a time-series/cross-section dataset. This study provides an alternative approach by using aggregate time-series data applied to theoretically consistent complete demand systems, thereby permitting a comparison of estimated economic effects (elasticities) across approaches.[9]

Some Estimation Issues

The NEP model and all thirteen special cases are estimated in a complete system of equations including FAFH, FAH, and alcoholic beverages using iterated nonlinear estimation techniques. Due to the singular nature of the share system one of the equations must be deleted in estimation (alcoholic beverages). The multivariate Fourier series requires all of its arguments to be within the $(0, 2\pi)$ interval, since sines and cosines are periodic functions. To ensure that the logarithms of prices are within this interval each was rescaled according to the following rule of $\ln \acute{p}_i = \ln p_i - \min(\ln p_i) + \in \ \forall\, i$ with $\in = 0.00001$ and a scaling factor adopted of $\lambda = \frac{6}{\max(\ln \acute{p}_i)}$ as suggested by Gallant (1982). This rescaling is of no consequence except to induce a change in units. Estimated elasticities are invariant to this rescaling. It is also necessary to select a set of multi-indexes determining the functional form of the Fourier flexible form.[10] Limiting attention to only simple interactions among prices

[9] Testing particular hypotheses about certain factors affecting demand for food other than prices and expenditures is beyond the scope of this analysis. The potential bias that may be caused by omitting these factors is acknowledged as a potential shortcoming and is left as a topic for further work.

[10] The choice of multi-indexes is an open question. For a discussion of this point see Gallant (1984).

amounts to three multi-indexes of the following form:

k_1	k_2	k_3
1	0	1
−1	1	0
0	−1	−1

Empirical Results

The estimated parameters for the fourteen models in the NEP class are reported in table 2. The signs of the pre-committed quantities (the $c_i's$) are nonnegative, conforming to our a priori beliefs.[11] Surveying the statistical significance of individual parameter estimates provides some insight into the appropriateness of some of the generalizations under consideration. Including pre-committed quantities appears justified with most of the $c_i's$ being individually statistically significantly different from zero. There may be less support for including the Fourier terms with only the GFAITL model having at least three of the six parameters that are individually statistically significantly different from zero. Some generalizations appear to lead to an over-parameterization with fewer parameters being individually statistically significantly different from zero (compare the AITL model to the AI or TL models).[12] There are also instances where a generalization leads to more parameters that are statistically significantly different from zero (compare the AI to GAI model and the AITL to GAITL model). This mixed evidence suggests that the merits of generalizing models needs to be evaluated on a case-by-case basis.

Model Comparisons: In-Sample Nested Tests

A primary motivation for nesting models is the convenience of using conventional hypothesis tests to evaluate the merits of a generalization by testing certain parameter restrictions—the NEP model includes a total of 43 generalizations.[13] Table 3 includes the results of testing these generalizations using likelihood ratio tests and reveals that only eight of the individual or collective restrictions fail to be rejected, suggesting that most generalizations were justified.

More specifically, the first column in table 3 reveals that ten of the thirteen nested models are rejected in favor of the NEP model. The models that are not rejected include the GFGAI, GAITL, and GAI models. The generalizations of the GFGAI, GAITL, and GAI models that result in NEP model do not statistically significantly contribute to the in-sample fit of the model, so one would prefer these nested models on grounds of parsimony. In choosing among these models, the nested tests prove helpful since the GAI model is a nested special case of both the GFGAI and GAITL models (see the sixth row of table 3). Separate tests fail to reject the GAI model against the alternatives of the GAITL and GFGAI models, respectively. Thus, the GAI model surfaces as the "preferred" model since it is statistically indistinguishable from both models and it is more parsimonous. This in-sample evidence favoring the GAI model implies that not much is gained from further generalizations of nesting the TL model or adding the Fourier terms, either separately, or together. To add weight to this observation, nesting the TL is also not a statistically significant generalization when added to the AI and GFGAI models and one fails to reject the proposition that the Fourier terms are jointly significantly different from zero when added to the GAITL and GTL models. The popular AI and TL models are rejected in favor of all of their more general counterparts except for the generalization to the AITL model.

Estimates of Elasticities

Another criterion to consider in models of varying generality is to assess how much estimated elasticities vary across models (a measure of the potential bias from using an incorrect form) and whether the elasticity estimates appear reasonable. Comparing estimated elasticities across rows in table 4 reveals that the magnitude of elasticities (but not sign) vary substantially across alternative functional forms. This is made clearly apparent by comparing estimates from the LES model with other models. Given that all of the nested tests reject the LES model and the outlier status that each of the estimated elasticities could be assigned, estimates from this model are omitted from further discussion concerning ranges.

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[11] Only the estimate of c_3 in the GFGTL model is negative. The magnitude of the other $c_i's$ in this model was large enough to ensure that there is a nonnegative amount of subsistence expenditure.

[12] Over-parmeterization is not only prohibitive in terms of reducing degrees of freedom it can also impact the precision with which the estimated economic effects (elasticities) are measured.

[13] By construction a more general model will have a better in-sample fit than its nested counterpart. The question of interest is whether this improvement is statistically significant.

Table 2. Estimated Coefficients for Models in the NEP Class

	NEP	GFGAI	GAITL	GFAITL	GFGTL	GAI	GFAI	AITL	GFTL	GTL	AI	TL	GFLES	LES
δ	29.096	65.007	8.245*	6.128*	–	30.106*	4.233*	−30.838	–	–	6.633*	–	–	–
	(34.161)	(61.844)	(0.670)	(0.331)	–	(11.113)	(1.925)	(118.665)	–	–	(1.453)	–	–	–
α_1	−12.233	−31.081	0.868	−12.066*	8.075*	−11.576*	2.054	−8.147	4.599*	2.335*	0.426	4.135*	0.059	−0.219*
	(10.175)	(19.783)	(3.582)	(3.099)	(1.407)	(3.945)	(1.356)	(31.881)	(0.386)	(0.765)	(0.899)	(0.300)	(0.220)	(0.066)
α_2	42.333	55.665	8.847	22.447*	−11.439*	23.102*	−1.665	5.736	−5.164*	−2.885*	0.496	−4.793*	1.118*	1.407*
	(45.832)	(42.455)	(5.466)	(4.396)	(1.626)	(7.569)	(1.820)	(25.656)	(0.471)	(0.915)	(1.288)	(0.418)	(0.205)	(0.084)
γ_{11}	−52.240	−28.578	−0.731	7.267	14.586	5.580*	5.300	−4.473	6.275*	−0.441	0.131	0.646*	–	–
	(67.016)	(33.203)	(0.888)	(4.669)	(7.847)	(2.387)	(3.148)	(5.886)	(2.745)	(0.383)	(0.639)	(0.030)	–	–
γ_{12}	50.347	20.265	−1.231	−7.628	−12.464	−12.188*	−4.445	4.366	−5.401*	0.461	−0.121	−0.254*	–	–
	(63.946)	(30.441)	(2.931)	(4.657)	(7.702)	(3.904)	(3.220)	(4.111)	(2.686)	(0.310)	(0.912)	(0.030)	–	–
γ_{22}	2.112	14.558	2.283	11.627*	12.047	23.532*	3.648	−4.716	4.373	−1.363*	0.109	−0.564*	–	–
	(6.453)	(28.317)	(1.959)	(4.893)	(7.735)	(6.620)	(3.438)	(2.770)	(2.668)	(0.364)	(1.303)	(0.099)	–	–
γ_{13}	15.862	–	10.883	−1.555*	−0.959	–	–	0.980	−0.285	0.380*	–	0.165*	–	–
	(80.076)	–	(6.767)	(0.589)	(0.996)	–	–	(1.557)	(0.312)	(0.115)	–	(0.011)	–	–
γ_{23}	−65.246	–	−8.904*	−0.619	−1.317*	–	–	−0.710	0.225*	0.210	–	0.024	–	–
	(81.584)	–	(3.819)	(0.479)	(0.652)	–	–	(1.201)	(0.110)	(0.120)	–	(0.019)	–	–
β_1	−0.282	−0.444*	−0.360	−1.816*	–	−0.479*	−0.671*	0.384	–	–	−0.624*	–	–	–
	(0.408)	(0.177)	(0.305)	(0.232)	–	(0.107)	(0.067)	(0.433)	–	–	(0.065)	–	–	–
β_2	1.488*	0.904*	1.513*	2.927*	–	0.904*	0.917*	−0.328	–	–	0.894*	–	–	–
	(0.423)	(0.262)	(0.354)	(0.275)	–	(0.142)	(0.089)	(0.418)	–	–	(0.091)	–	–	–
c_1	310.621*	309.738*	292.141*	–	23.218	304.175*	–	–	–	295.449*	–	–	314.150*	262.108*
	(26.607)	(16.332)	(22.351)	–	(71.561)	(11.553)	–	–	–	(22.564)	–	–	(26.966)	(19.419)
c_2	190.503*	201.040*	197.243*	–	466.625*	196.753*	–	–	–	157.409*	–	–	495.867*	696.566*
	(35.798)	(20.758)	(31.788)	–	(74.285)	(12.537)	–	–	–	(24.858)	–	–	(208.539)	(34.154)
c_3	73.160*	60.633*	70.343*	–	−86.780*	61.629*	–	–	–	65.258*	–	–	65.810*	15.076*
	(22.182)	(12.507)	(22.101)	–	(30.696)	(6.995)	–	–	–	(7.315)	–	–	(30.250)	(4.291)
υ_1	−2.147	−1.603	–	0.258	0.354	–	0.203	–	0.184	–	–	–	−0.017	–
	(2.370)	(1.226)	–	(0.164)	(0.267)	–	(0.108)	–	(0.096)	–	–	–	(0.016)	–
υ_2	0.210	0.177	–	0.034*	0.062	–	0.014	–	0.013	–	–	–	0.001	–
	(0.145)	(0.108)	–	(0.016)	(0.032)	–	(0.011)	–	(0.010)	–	–	–	(0.003)	–
υ_3	0.643	0.187*	–	−0.018*	−0.016	–	−0.010*	–	−0.007*	–	–	–	0.014	–
	(0.922)	(0.083)	–	(0.006)	(0.009)	–	(0.004)	–	(0.003)	–	–	–	(0.024)	–
ν_1	−0.762	−0.652	–	0.044	0.088	–	0.054	–	0.047*	–	–	–	0.009	–
	(0.765)	(0.370)	–	(0.036)	(0.068)	–	(0.028)	–	(0.023)	–	–	–	(0.007)	–
ν_2	−0.287*	−0.168	–	−0.028*	−0.049*	–	−0.012	–	−0.012	–	–	–	0.001	–
	(0.134)	(0.086)	–	(0.011)	(0.023)	–	(0.008)	–	(0.007)	–	–	–	(0.003)	–
ν_3	0.019	−0.169*	–	0.008	−0.010	–	0.007*	–	0.005	–	–	–	0.004	–
	(0.320)	(0.078)	–	(0.005)	(0.012)	–	(0.004)	–	(0.003)	–	–	–	(0.008)	–

Notes: Numbers in parentheses are the estimated standard errors and * denotes a coefficient that is statistically significantly different from zero at the 5% level.

Table 3. Log-Likelihood Values and Likelihood Ratio Tests for Models in the NEP Class

	NEP	GFGAI	GAITL	GFAITL	GFGTL	GAI	GFAI	AITL	GFTL	GTL	AI	TL	GFLES	LES
NEP	276.756													
	19													
GFGAI	1.44	275.732												
	(2)	*17*												
GAITL	9.48		270.016											
	(6)		*13*											
GFAITL	8.13*			270.978										
	(3)			*16*										
GFGTL	9.73*				269.840									
	(3)				*16*									
GAI	11.43	10.65	2.21			268.631								
	(8)	(6)	(2)			*11*								
GFAI	18.36*	17.67*		10.92*			263.699							
	(5)	(3)		(2)			*14*							
AITL	28.77*		21.86*	22.01*				256.301						
	(9)		(3)	(6)				*10*						
GFTL	17.40*			9.89*	8.18*				264.386					
	(6)			(3)	(3)				*13*					
GTL	20.95*		13.00*		11.97					261.858				
	(9)		(3)		(6)					*10*				
AI	31.91*	31.82*	25.42*	25.37*		24.12*	15.05*	3.77			254.067			
	(11)	(9)	(5)	(8)		(3)	(6)	(2)			*8*			
TL	32.03*		25.56*	25.50*	23.79*			3.92	16.58*	13.29*		253.980		
	(12)		(6)	(9)	(9)			(3)	(6)	(3)		*7*		
GFLES	23.08*	22.60*			14.24*								260.345	
	(8)	(6)			(5)								*11*	
LES	48.79*	49.45*	44.55*		41.67*	44.01*				33.41*			30.28*	242.061
	(14)	(12)	(8)		(11)	(6)				(5)			(6)	*5*

Notes: Diagonal elements are the maximized log-likelihood values and italicized elements under each diagonal element indicate the number of parameters in the model. Off-diagonal elements and numbers in parentheses are the test statistic ($LR^{\#}$) and number of restrictions between the more general model and the nested model, respectively. A small sample correction was applied (see Bohm, Rieder, and Tinter and Bewley) in calculating the test statistic so that $LR^{\#} = -2[(MT - k)/MT](L^R - L^U)$ where M is the number of estimated equations, T is sample size, k is the number of parameters in the unrestricted model, L^R is the maximized log-likelihood value of the restricted model and L^u is the maximized log-likelihood value of the unrestricted model. * denotes a significant test statistic at the 5% level using the following critical values $\chi_2 = 5.991$, $\chi_3 = 7.815$, $\chi_5 = 11.070$, $\chi_6 = 12.592$, $\chi_8 = 15.507$, $\chi_9 = 16.919$, $\chi_{11} = 19.675$, $\chi_{12} = 21.026$, and $\chi_{14} = 23.685$.

Table 4. Price and Expenditure Elasticities

	NEP	GFGAI	GAITL	GFAITL	GFGTL	GAI	GFAI	AITL	GFTL	GTL	AI	TL	GFLES	LES	Min	Max
Price elasticities																
η_{hh}	−0.54	−0.54	−0.44	−0.29	−0.27	−0.46	−0.24	−0.26	−0.23	−0.32	−0.24	−0.22	−0.32	−0.07	−0.54	−0.22
η_{ha}	0.34	0.33	0.31	0.19	0.16	0.31	0.40	0.32	0.38	0.38	0.37	0.34	0.43	0.48	0.16	0.43
η_{hb}	0.13	0.14	0.16	0.17	0.17	0.15	0.13	0.12	0.13	0.15	0.08	0.09	0.12	0.01	0.08	0.17
η_{ah}	−0.79	−0.80	−1.05	−1.23	−1.30	−1.04	−1.43	−1.43	−1.44	−1.34	−1.42	−1.44	−1.30	−1.62	−1.44	−0.79
η_{aa}	−1.37	−1.36	−1.50	−1.23	−1.16	−1.50	−2.03	−1.84	−1.95	−1.84	−1.97	−1.91	−2.01	−2.33	−2.03	−1.16
η_{ab}	−0.28	−0.28	−0.24	−0.33	−0.33	−0.20	−0.16	−0.20	−0.17	−0.22	−0.17	−0.19	−0.21	−0.08	−0.33	−0.16
η_{bh}	0.58	0.61	0.84	0.79	0.89	0.79	0.91	1.02	0.90	1.05	0.84	0.89	0.89	0.61	0.58	1.05
η_{ba}	0.34	0.36	0.62	0.32	0.36	0.70	1.18	1.04	1.14	0.96	1.20	1.11	1.03	1.75	0.32	1.20
η_{bb}	−0.91	−0.94	−1.09	−0.87	−0.87	−1.12	−1.08	−0.87	−1.07	−0.99	−0.84	−0.82	−0.97	−0.82	−1.12	−0.82
Expenditure elasticities																
η_{hM}	0.07	0.07	−0.03	−0.07	−0.06	0.00	−0.29	−0.18	−0.27	−0.20	−0.20	−0.21	−0.23	−0.42	−0.29	0.07
η_{aM}	2.45	2.45	2.78	2.79	2.80	2.75	3.62	3.48	3.55	3.40	3.55	3.54	3.51	4.03	2.45	3.62
η_{hM}	−0.01	−0.02	−0.37	−0.24	−0.39	−0.38	−1.01	−1.19	−0.97	−1.03	−1.20	−1.19	−0.95	−1.54	−1.20	−0.01
Consistency with theory																
NSD	71.9	71.9	75.0	68.8	68.8	71.9	87.5	100.0	96.9	100.0	100.0	100.0	100.0	100.0	68.75	100.00

Notes: η_{ij} are the Marshallian price elasticities of demand for the ith good with respect to the jth price, respectively, and η_{iM} are the expenditure elasticities for the ith good where $i = h$ for food-at-home (FAH), a for food-away-from-home (FAFH), and b for alcoholic beverages. The reported estimates are the respective means from elasticities calculated over the sample. *NSD* is the percentage of observations that satisfy curvature (negative semi-definiteness of the substitution matrix) over the sample. The estimates for the LES model were discarded in calculating the minimum and maximum since this model was comprehensively rejected.

Overall, own-price elasticities appear reasonable and comply with the law of demand. The own-price elasticity of demand for the FAH (η_{hh}) was estimated to be price inelastic ranging from −0.54 to −0.22 across models. Among the models that were not rejected, estimates were more price elastic ranging from −0.54 to −0.44.[14] In comparison, the own-price elasticity of demand for the FAFH (η_{aa}) was estimated to be price elastic ranging from −2.03 to −1.16. Among the models not rejected estimates were less elastic ranging from −1.50 to −1.37.[15] Finally, the own-price elasticity of demand for alcoholic beverages (η_{bb}) varied the least across models ranging from −1.12 to −0.82.

The estimated cross-price elasticities of demand for FAH with respect to the price of FAFH (η_{ha}) range from 0.16 to 0.43 implying that they are gross substitutes. The estimated cross-price elasticity of demand for FAFH with respect to the FAH price (η_{ah}) ranges from −1.44 to −0.79 implying that they are gross compliments. The large expenditure effect for FAFH outweighs the positive substitution effect favoring FAFH consumption as a replacement for FAH when the price of FAH increases. The large expenditure effect for FAFH also dominates the cross-price elasticity for FAFH with respect to alcoholic beverage price (η_{ab}) which finds these goods are gross complements. Finally, the cross-price elasticities of the demand for alcoholic beverage consumption with respect to changes in FAH price (η_{ba}) and FAFH (η_{ba}) price are positive across models implying these goods are gross substitutes.

The estimated expenditure elasticities confirm the growing importance of FAFH in the food budget compared to FAH and alcoholic beverages. The expenditure elasticities for FAH (η_{hM}) are very small and provide the only instance where estimates change signs across models. The expenditure elasticities for alcoholic beverages (η_{bM}) are negative and sensitive to functional form ranging from −1.20 to −0.01. The expenditure elasticities for FAFH (η_{aM}) are large and range from 2.45 to 3.62 across models. For the models that we fail to reject, the estimates vary from 2.45 to 2.78.

Recall that the literature has taken considerable interest in FAFH consumption and has provided detailed estimates concerning FAFH income elasticities. Byrne, Capps, and Saha provide a table with previous estimates of this income elasticity that range from 0.11 to 0.36 which their estimates also fall within (around 0.2). Park et al. estimated this income elasticity to be 1.12 for poverty status households and 0.61 for non-poverty status households. The expenditure elasticities shown in table 4 are not directly comparable to these previous estimates. To convert these expenditure elasticities to income elasticities we need to make use of the following relationship $\frac{\partial q_i}{\partial Y} = \frac{\partial q_i}{\partial M} \cdot \frac{\partial M}{\partial Y}$ or in elasticity form $\eta_{iY} = \eta_{iM} \cdot \eta_{MY}$, where q_i is the quantity demanded of the ith good, Y denotes income, M denotes expenditure on food, η_{iY} denotes the income elasticity of demand for the ith commodity, η_{iM} is the food expenditure elasticity for the ith commodity, and η_{MY} is the income elasticity of demand for the total expenditure on food. An estimate of η_{MY} was obtained with an auxiliary regression of per capita food expenditures on per capita disposable income which resulted in an estimated income elasticity of demand for food expenditures of 0.332.[16] Based on this estimate the range of income elasticities for FAFH across all models is 0.813 to 1.202. The subset of the models with expenditure elasticities below the threshold 3.01 for an income elasticity of demand that is less than 1 includes all the models that are not rejected, with implied income elasticities ranging from 0.813 to 0.930. These estimates are more elastic and outside the range of estimates shown in Byrne, Capps, and Saha and more consistent with those of Park et al.

Finally, to investigate how the underlying consistency with demand theory might be affected by generalizing models, the percentage of observations satisfying curvature over the sample is also reported in table 4. The results reveal that more general models are less consistent with curvature over the sample. Less general models satisfied curvature globally, whereas in more general models, the percentage of observations that satisfied curvature declined to as low as 69%. This finding

[14] Finding FAH consumption to be fairly inelastic to price seems reasonable given that this includes the purchase of household staples and accounts for a declining component of the household budget and so has a smaller expenditure effect.

[15] Finding FAFH consumption to be price elastic confirms the common practice of using price incentives as a marketing tool for these goods. In addition, FAFH accounts for a growing proportion of the household budget and so there is a substantial expenditure effect that contributes to this price responsiveness.

[16] To implement this auxiliary regression the following equation using data over the period 1968–99 was estimated: $\ln(M/\text{CPI}) = 1.3265 + 0.7318 * \ln(P_{\text{food}}/\text{CPI}) - 0.2832 * \ln(P_{\text{nonfood}}/\text{CPI}) + 0.3320 * \ln(Y/\text{CPI})$ where M is per capita food expenditures, CPI is the Consumer Price Index for all goods, P_{food} is the CPI for all food and beverages, P_{nonfood} is the CPI for all goods excluding food, Y is per capita disposable income.

suggests that a more general model does not necessarily imply a *better* model in the sense that estimated economic effects may become less consistent with demand theory.

Model Comparisons: Out-of Sample Forecasting Performance

So far, attention has been limited to in-sample criteria to evaluate alternative models of varying degrees of generality. An additional justifiable criterion for model selection is out-of-sample forecasting accuracy. Kastens and Brester note that out-of-sample fit is rarely considered in the context of demand models and make the point (citing Waugh) that surely a "good" model is one that does a reasonable job of conditional forecasting. The point of this section is to investigate how generalizing demand systems affects out-of-sample forecast errors and whether this criterion can provide further information in deciding upon a "preferred" model.[17]

Due to the small sample size on hand and to conserve degrees of freedom one-period forecasts are used to evaluate each model's ability to forecast out-of-sample.[18] To outline how these one-period forecasts are generated it is useful to rewrite (2), more succinctly as

$$s_t = f(\pi, z_t) + u_t \quad t = 1, 2, \ldots, T \tag{3}$$

where $s_t = (s_{1t}, s_{2t}, \ldots, s_{(N-1)t})'$, $u_t = (u_{1t}, u_{2t}, \ldots, u_{(N-1)t})'$, π is the included parameters, and z_t the included exogenous variables. The one-period forecast at time k, $\widehat{s_k}$, is generated by reestimating the model using a subsample of $(T-1)$ observations, omitting the kth observation (i.e., s_k and z_k) and generating an estimate of $\hat{\pi}$. This estimate of $\hat{\pi}$ is used to generate the one-period forecast according to $\widehat{s_k} = f(\hat{\pi}, z_k)$. This procedure is repeated a total of T times (i.e., $k = 1, 2, \ldots, T$) generating a sample of T one-period forecasts. The resulting one-period $(N-1)$-forecast vector $\widehat{s_t} = (\widehat{s_{1t}}, \widehat{s_{2t}}, \ldots, \widehat{s_{(N-1)t}})'$ can be used to calculate the $(N-1)$-vector of forecast errors $\widehat{u_t} = (\widehat{u_{1t}}, \widehat{u_{2t}}, \ldots, \widehat{u_{(N-1)t}})'$ by calculating $\widehat{u_t} = s_t - \widehat{s_t}$.

Since the idea is to use forecasting performance to provide further information in choosing a preferred model by ranking alternative models performance, a statistic utilizing all of the information contained in this forecast error vector, $\widehat{u_t}$, is needed.[19] A single statistic accounting for the information contained in $\widehat{u_t}$ permitting a definitive ranking among models based upon a particular criterion is desired. Forming the $(N-1)\times(N-1)$ matrix $\Omega^j = \widehat{u_t}^j \widehat{u_t}^{j\prime}$ is an alternative way to express the forecasting accuracy of the jth model contained in $\widehat{u_t}^j$.[20] From this matrix several statistics can be calculated, such as the trace, $\mathrm{tr}(\Omega^j)$, which is equivalent to the sum of squared forecast errors (SSFE) for the $(N-1)$ equations (i.e., $\mathrm{tr}(\Omega^j) = \sum_{i=1}^{N-1} \widehat{u_{it}}^{j\prime} \widehat{u_{it}}^j = \sum_{i=1}^{N-1}\sum_{t=1}^{T}[\widehat{u_{it}}^j]^2$). This statistic permits models to be ranked based upon which has the smallest SSFE. Another statistic summarizing this multivariate phenomenon is the determinant, $|\Omega^j|$.[21] We can ascertain from the formula of the determinant for the case of $N = 3$, that the correlation between forecast errors across equations, has a favorable affect by making this statistic smaller. Thus, models producing out-of-sample forecast errors that are contemporaneously correlated across equations benefit under the $|\Omega^j|$ compared to $\mathrm{tr}(\Omega^j)$ where this correlation is not taken into account. It is important to note that these alternative statistics across competing models will not necessarily be ranked in the same order [smallest (best) to largest (worst)] even if the forecast errors across equations are uncorrelated, since $\mathrm{tr}(\Omega^j)$ involves the sum of the SSFE in each equation and $|\Omega^j|$ involves the product of the SSFE.[22]

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[17] This out-of-sample performance criterion has an advantage over the in-sample nested hypothesis tests in that models need not be nested in order to be compared. It is also worth noting that generalizing a model does not necessarily imply smaller out-of-sample forecast errors unlike in-sample residuals.

[18] One-period forecasts are commonly used in the literature to evaluate model performance and out-sample forecasting accuracy (see Ashley, Goodwin, Bradshaw and Orden, and Chambers and Nowman).

[19] Because we are dealing with a system of equations and have a $(N-1)$–vector of forecast errors, commonly used measures such as root mean squared errors (RMSE) or mean absolute error (MAE) in the univariate setting are less useful. These measures would result in $(N-1)$ pair-wise comparisons if we calculated them for each equation.

[20] This matrix is analogous to the variance-covariance matrix that is calculated using in-sample residuals but is calculated using out-of-sample one-period forecast errors.

[21] The criterion of making the determinant of the matrix of residual sum of squared errors and cross-products small, is precisely the criterion used in maximum likelihood estimation applied to the log of the joint normal densities of in-sample disturbances to generate parameter estimates (see Greene, p. 496).

[22] This possibility of differences in ordering stems from $\mathrm{tr}(\Omega^j) = \sum_{i=1}^{N-1}\tau_i^j$ while $|\Omega^j| = \tau_1^j \cdot \tau_2^j \cdot \tau_3^j \ldots \tau_{N-1}^j$ where τ_i^j is the ith eigenvalue of Ω^j. This facet of evaluating forecast accuracy and rankings being conditional on the criterion chosen is well established in the case of $\widehat{u_t}$'s univariate counterparts. For instance, for two commonly used measures RMSE and MAE, it is well known that

Table 5. One-Period Out-of-Sample Forecasting Performance

Model	Number of Parameters	Estimates		Rankings	
		$\mathrm{tr}(\Omega^j)$	$\lvert\Omega^j\rvert$	$\mathrm{tr}(\Omega^j)$	$\lvert\Omega^j\rvert$
NEP	19	4.081E-03	8.783E-07	GFGAI	GFGAI
GFGAI	17	3.816E-03	3.270E-07	GAITL	GAI
GAITL	13	3.851E-03	6.601E-07	NEP	GFAITL
GFAITL	16	5.840E-03	5.304E-07	GAI	AITL
GFGTL	16	6.104E-03	8.591E-07	GFAITL	GTL
GAI	11	4.290E-03	3.769E-07	GFGTL	GAITL
GFAI	14	7.937E-03	8.369E-07	AITL	TL
AITL	10	6.332E-03	5.606E-07	GTL	GFTL
GFTL	13	7.368E-03	7.351E-07	TL	AI
GTL	10	6.558E-03	5.744E-07	GFTL	GFLES
AI	8	8.102E-03	7.919E-07	GFLES	GFAI
TL	7	7.262E-03	7.319E-07	GFAI	GFGTL
GFLES	11	7.749E-03	8.221E-07	AI	NEP
LES	5	9.408E-03	1.311E-06	LES	LES

For each of the fourteen models in the NEP class, the above procedure for generating the $(N-1)$-vector of one-period forecast errors was undertaken and the corresponding matrix Ω^j was formed, permitting $\mathrm{tr}(\Omega^j)$ and $|\Omega^j|$ to be calculated. The estimates are shown in table 5 as well as the ranking of models according to each criterion ordered smallest (best) to largest (worst). The GFGAI model outperforms all the other models under both criteria. The three models that were not rejected in favor of the NEP model (the GFGAI, GAITL, and GAI models) ranked in the top four along with the NEP model based on $\mathrm{tr}(\Omega^j)$. Two of these models, the GFGAI and GAI models, ranked first and second, respectively, based on $|\Omega^j|$. Thus, the in-sample nested tests and out-of-sample forecast accuracy results conform well in identifying at least a subset of "preferred" models.

To assess how generalizing demand systems affect out-of-sample forecasting errors more generally and how the statistics track with each other, plots of $\mathrm{tr}(\Omega^j)$ and $|\Omega^j|$ across models are shown in figure 2. Both criteria exhibit a positive trend reading left (more general) to right (less general) reflecting the phenomena that the more general models tend to produce more accurate out-of-sample forecasts.[23] However, the saw-tooth nature of the plots for both statistics reveals increased generality does not necessarily improve out-of-sample forecast accuracy. This reinforces previous statements that generalizing models need to be evaluated on a case-by-case basis despite the observation that more general models tend to have better forecasting accuracy. The final striking feature of figure 2 is how well the statistics track each other.

RMSE penalizes larger errors compared to the MAE and as a consequence can also result in alternative rankings.

[23] The trend in $|\Omega^j|$ has been accentuated due to rescaling by 10^4.

The Preferred Model

The in-sample and out-of-sample evidence agrees on identifying a subset of preferred models that includes the NEP, GFGAI, GAITL, and GAI models. The nested hypothesis tests find that the GAI model is statistically indistinguishable from the other models in this subset. Thus, in-sample evidence favors the simpler GAI model on grounds of parsimony. The out-of-sample evidence favors the GFGAI model under both criteria, with the GAI model being ranked fourth using $\mathrm{tr}(\Omega^j)$ and second using $|\Omega^j|$. A useful next step, though beyond the scope of this article, is to develop inference procedures for these out-of-sample statistics.[24] Without the ability to test inferences on the out-of-sample results to delineate between the GFGAI and GAI models, we cannot say whether the GFGAI out-of-sample performance is statistically better than the GAI model. Pending the outcome of such inferences,

[24] Ashley has developed such inference procedures for post-sample model selection appropriate for the univariate case utilizing a bootstrap. Additional work is currently focusing on developing inference procedures applicable to post-sample model selection for the multivariate case required for the models in this paper.

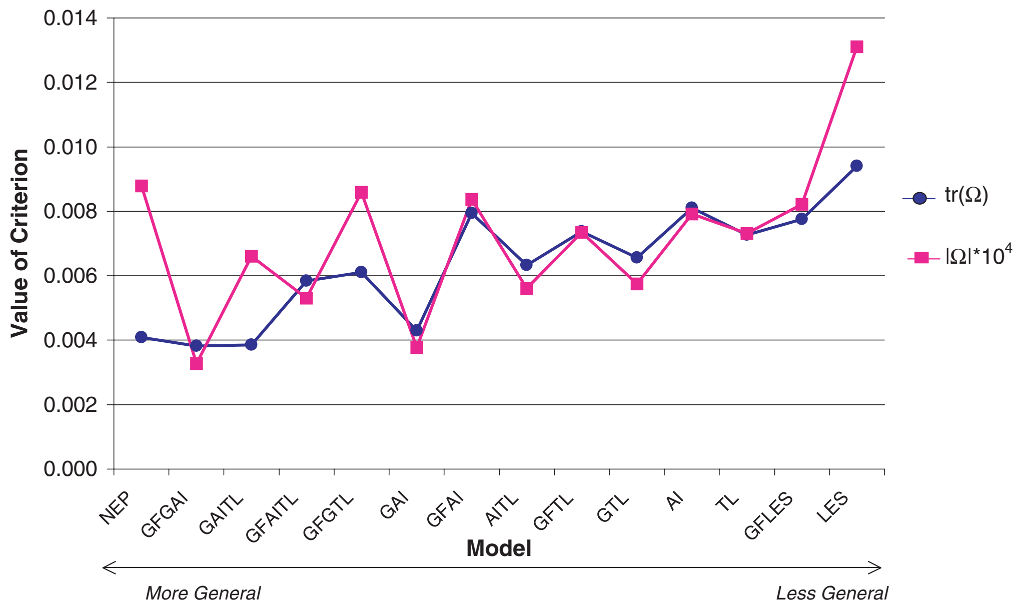

Figure 2. Comparision of out-of-sample forecasting performance across models based on tr(Ω^j) and $|\Omega^j|$

and depending on the weights placed upon the in-sample versus out-of-sample results, one could favor either the GFGAI or GAI model as the "preferred" model. However, it is reassuring to the applied researcher who is unable to settle on whether to use estimates from the GFGAI or GAI model in welfare or policy analysis that the estimated elasticities are quite similar.

Conclusion

The NEP model presents a unifying generalization of flexible functional form specifications used in demand analysis in an effort to identify a better model. The NEP model is derived by combining the three generalizations used previously—pre-committed quantities, nesting the AI and TL models, and nesting the Fourier flexible functional form. This new model and its nested counterparts are used to estimate models for U.S. food demand that includes FAH, FAFH, and alcoholic beverages.

Results suggest that generalizing the models has the merit of leading to statistically significant improvements to the in-sample-fit and improved out-of-sample forecasting accuracy. However, after a certain amount of model-enhancing generalizations, statistically insignificant improvements to in-sample-fit and even poorer out-of-sample forecast accuracy can occur. Thus, a more general model does not necessarily imply a statistically *better* model. Furthermore, more general models tended to be less consistent with demand theory satisfying curvature less than globally over the sample.

Differences in the magnitude of estimated elasticities across models confirm that estimates can be "fragile" and that employing the wrong functional form may result in significant bias. However, these differences are smaller among the subset of models that are not rejected. Based on the preferred GAI and GFGAI models, FAFH is estimated to be price and income elastic compared to FAH which was price and income inelastic. The implied income elasticity of demand for FAFH in this study is larger than most previous estimates. Rationalizing these differences is left for future work, the question of whether cross-sectional models under-estimate or whether aggregate time-series models over-estimate this income effect remains open.

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