A QUAIDS MODEL OF JAPANESE MEAT DEMAND

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Abstract

This paper makes a contribution to the application of nonlinear simultaneous equations estimation and nonparametric Bootstrapping techniques. The nonlinear demand model estimation work in this paper is in the context of the newly developed Quadratic Almost Ideal Demand System (QUAIDS) model, and provides substantive results in terms of both model estimation technique and empirical economic findings. For the first time, bootstrapping is used in this highly nonlinear modeling environment to estimate variability in demand model parameter estimates and associated demand elasticities. The application relates to Japanese consumer behavior relative to Wagyu Beef, Imported Beef, Pork, Chicken, and Fish demand, and the empirical results are highly relevant to U.S. exporters. The paper provides evidence of the substantially increased flexibility of the new model of consumer demand, and also illustrates the utility of using bootstrapping, as opposed to relying only on derivative based asymptotic approximations, for assessing the reliability of estimated results.

1. Introduction

Developing marketing strategies for meat products in Japan has been of great interest to U.S. domestic meat producers. Before the 1970's, less than 10% of the total beef consumed in Japan was imported. But in the 1970's and 1980's this number increased dramatically to 25%, and continued to rise further to around 50% in 1995. Furthermore, the relative percentage of imported beef quantities to total beef consumption in Japan is continuing to increase, now comprising more than half of all beef consumption. While beef import percentage fluctuated in the last three decades because of the outbreak of Mad Cow Disease in Europe, beef consumption the overall trend in consumption has been upward, not only because the increased per capita income makes meat more affordable, but also because of beef's more effectively satisfying calories intake, culinary preferences and greater availability of domestically produced livestock. Natsuki Fujita (1988) showed that meat replaced pulses, entering the top three calories supply sources in 1988 following behind fat and sugar, and provided 12.5% of total calories.

As the largest beef exporter to Japan, the U.S. is providing roughly 40 percent of the imported beef consumed by Japanese consumers. However, Japanese consumers pay four to five times more for beef than do U.S. consumers because of trade barriers and Japanese government intervention. The rate of protection afforded the beef industry by Japanese trade policy is ranked third below only the rice and dairy industries in order to protect agricultural interests, and prevent inefficient domestic beef producers from streaming into urban areas. The protections are also aimed at alleviating the growing disparity between urban and rural incomes in an attempt to enhance income levels in rural areas. Under past negotiations requested by the United Stated to remove those trade barriers in an effort to gain more convenient access to Japan's beef market for U.S. producers, the Japanese government signed the Beef Market Access Agreement (BMAA) regarding beef import policy in 1988, and agreed to comply with the terms of the Uruguay round of the General Agreement on Tariffs and Trade (GATT) negotiations.

The beef industry, however, is still afforded relatively high protection by the Japanese government to minimize the opposition of the politically powerful domestic beef producers. As a result, there has been some research on the economic effects of Japanese restrictive beef import policy (e.g., Anderson; Hayami; Wahl, Williams, and Hayes).

In this paper, a QUAIDS specification of Japanese meat demand is estimated with endogenous regressors and exact restrictions on model parameters. A methodological contribution is provided in the way of a Bootstrapping methodology for obtaining standard errors of parameters, as well as demand elasticities, in this highly nonlinear model specification. The methodology is briefly introduced in the context of a simultaneous equation models and then extended to incorporate microtheoretic restrictions. The results of the application are compared to results based on earlier estimates provided by Heckelei, Mittelhammer, and Wahl (1996).

This paper is structured as follows: the first section of this paper describes the overview of meat consumption in Japan, followed by the second section, which provides a data description. Section three presents the results of applying restricted nonlinear

GMM estimation and bootstrapping methodology to the QAIDS model of the Japanese meat sector. The final section offers some concluding comments on the major results.

2. Overview of Meat Demand in Japan

Beef consumption does not have a long history in Japan due to a dietary ban on the eating of flesh from four-legged animals before the Meiji Restoration (Yoshida and Klein, 1990). Consumption did not increase appreciably for 100 years even after the ban was lifted. Alternatively this island nation has been relying on rice, soybeans and fish as the main protein intake sources. Since World War II, however, the Japanese diet has become progressively more diversified where consumption of chicken and pork both increased with beef consumption also increasing, but at much slower pace. The reasons for these changes in meat consumption pattern are thought to be mainly due to rising incomes, greater exposure to Western cooking, and greater availability of domestically produced livestock. The major way in which increased income affects the composition of the food basket is to promote substitution of higher-priced food groups for low-priced staples implying an increase in nutrient quality of food consumption, and diversification of food composition in the consumption basket.

To illustrate the magnitude of these consumption changes, between 1962 and 1986, chicken consumption in Japan grew by 900 percent, and increases in pork and beef consumptions were 275 percent and 200 percent respectively, while per capita fish consumption remained fairly steady, increasing a mere 19 percent. In 1965, the per capita consumption of beef, pork and chicken meat were nearly equal at about 1 to 2 kilograms per year. By 1986, per capita beef, pork and chicken meat consumption had increased to 4.1 kilograms, 9.9 kilograms and 9.8 kilograms respectively. Since then, beef consumption has kept rising steadily and slowly, while pork and chicken consumption decreased slightly. Throughout the period from 1965 to 2000, the widespread modern confinement feeding technology for hogs and chicken promoted very rapid supply growth of these two meats, reducing cost and prices, and thereby promoting consumption. The disparity in growth rates for beef, pork and chicken reflected the fact of historically restrictive beef import quota, which resulted in persistent increase in beef prices. Meanwhile, the Japanese continued to consume a large amount of fish products, spending as much on marine products as they do on beef, pork, and chicken meat combined.

In this paper, import-quality beef and Wagyu beef are treated as separate commodities in the model (Hayes, Wahl, and Williams). The Japanese favor heavily marbled cuts of beef and this unique type of preference originated from religious, historical and cultural influences. The prices consumers are willing to pay for beef increases as the degree of marbling increases. On the other hand, a much longer feeding period for Wagyu beef to raise intramuscular fat also results in substantially higher production costs and beef prices relative to alternatives. Dairy beef are fed for shorter periods of time and are slaughtered with considerably less marbling than Wagyu animals. Dairy beef in Japan is similar to imported-quality beef from American, Australian, and Western Europe. Given the preceding observations, a wide price band can be expected, and is observed for different qualities of beef with Wagyu beef price ranking highest by a considerable margin. The significantly greater similarity between the beef imported from the United States and Japanese dairy steer beef than between imported U.S. beef and Wagyu steer beef provided legitimacy to the separation of Wagyu beef from dairy beef.

3. The QUAIDS Model: Background

The empirical analysis employs a Quadratic AIDS model of Japanese meat demand. Deaton and Muellbauer (1980) combined the translog and Rotterdam models into the Almost Ideal Demand System (AIDS) that is touted to possess the best properties of the two, including approximating any demand system arbitrarily to first-order, aggregating perfectly over consumers, satisfying the axioms of choice, and capable of testing the restrictions of homogeneity and Slutsky symmetry. Since then, the AIDS model has arguably become the most widely used systems approach for modeling consumption behavior for grouped commodities.

However, the AIDS model has difficulty capturing the effects of non-linear Engel curves, as observed in various empirical demand studies. In order to maintain the attractive properties of AIDS model, while maintaining consistency with both Engel curve and relative price effects within a utility maximization framework (A. Lewbel, 1997), a quadratic term in log income is added to AIDS model and leads to the Quadratic AIDS (QUAIDS) model specification. Increased flexibility of the demand system representation is thus achieved in a parsimonious way through the addition of the quadratic term.

Gorman (1981) proved that for demand models, the generalized linear form of rank two (where rank is the maximum dimension of the function space spanned by the Engel curves of the demand system; see Lewbel, 1991) is a necessary and sufficient condition for aggregate demands to resemble representative agent models in certain ways. Rank two demands models include Linear AIDs, translog, linear expenditure, quasihomothetic, Price-Independent Generalized Linear (PIGL) and Price-Independent

Generalized Log (PIGLOG) systems. However, as R. Cooper and K. Mclaren (1996) discovered, these locally flexible functional forms possess a relatively small regular region, and oftentimes they can only provide a local approximation within a small size neighborhood of the true data-generation function. More specifically, the translog has been criticized for mistakenly classifying goods as complements when they are actually substitutes, and it loses its flexibility when semidefiniteness (curvature) is imposed (Diewert and Wales, 1987), while the Linear Expenditure System has been criticized for its additive preference structure.

From these problems, the development of globally flexible functional forms that have larger regular regions and higher rank has grown very rapidly. Among other things, examples of such functions include the Laurent models (Barnett, 1985, 1987) and the General Exponential Form (GEF) of R. Cooper and K. McLaren (1996), which may be easily constrained to be regular over an unbounded region and subsume all of the points in any given sample.

Meanwhile, Lewbel focused his attentions on the rank of demand systems. Most locally flexible demand systems have rank two or less and are linear in the log of total expenditure. To accommodate nonlinear Engel curves, the nonlinear terms are restricted to be a quadratic in log income to provide a significantly better fit of budget shares to changing income levels while remaining a parsimonious model specification. The Quadratic Almost Ideal Demand System (QUAIDS) has rank three, and can better approximate non-linear Engel curves in empirical analysis. Since a QUAIDS model produces a considerably larger regular region than the locally flexible forms, it can be classified as effectively globally regular, where corresponding utility and indirect functions, and cost functions satisfy their theoretical properties for all non-negative demand, price and all utility levels as appropriate.

There is still one empirical paradox regarding QUAIDS. Empirical findings suggest that most agents have PIGLOG demands, implying that Engel curves must be quasihomothetic, i.e., linear in expenditure, for aggregate demand to resemble a utility maximizing representative consumer. On the other hand, the rank three cross sectional Engel curves are far from quasihomothetic, i.e., nonlinear in expenditure. Lewbel (1991) solved the paradox by proving theoretically that the presence of relatively few non-PIGLOG households is swamped by the majority of PIGLOG households. Lewbel (1991) compared the exact aggregation models and the representative consumer models using U.K. and U.S. individual household expenditures data from 1970 to 1984, and found that the two different types of models gave similar results regarding model fit, and price and income elasticities.

4. The QUAIDS Model: Functional Specification

Define the indirect utility for J commodities as

(1) $$\ln V = \left\{ \left[\frac{\ln m - \ln a(p)}{b(p)} \right]^{-1} + \lambda(p) \right\}^{-1}$$

where

(2) $$\ln a(p) = \alpha_0 + \sum_{i=1}^{J} \alpha_i \ln p_i + \frac{1}{2} \sum_{i=1}^{J} \sum_{j=1}^{J} \gamma_{ij} \ln p_i \ln p_j$$

(3) $$b(p) = \prod_{i=1}^{J} p_i^{\beta_i}$$

and

(4) $$\lambda(p) = \sum_{i=1}^{J} \lambda_i \ln p_i, \qquad where \sum_{i=1}^{J} \lambda_i = 0$$

By Roy's Identity the budget shares are given by:

(5) $$w_i = \frac{\partial \ln a(p)}{\partial \ln p_i} + \frac{\partial \ln b(p)}{\partial \ln p_i}\left(\ln x\right) + \frac{\partial \lambda}{\partial \ln p_i}\frac{1}{b\left(p\right)}\left(\ln x\right)^2$$

and the corresponding expenditure share equation is

(6) $$w_i = \alpha_i + \sum_{j=1}^{J} \gamma_{ij} \ln p_j + \beta_i \ln\left[\frac{m}{a(p)}\right] + \frac{\lambda_i}{b(p)}\left\{\ln\left[\frac{m}{a(p)}\right]\right\}^2 + \varepsilon_i$$

where w_i is the share of group expenditure allocated to product i, p_j is the price of product j, and m is the per capita expenditures on all commodities.

Differentiate equation (6) with respect to $\ln m$ and $\ln p_j$, respectively, to obtain

(7) $$\mu_i \equiv \frac{\partial w_i}{\partial \ln m} = \beta_i + \frac{2\lambda_i}{b(p)}\left\{\ln\left[\frac{m}{a(p)}\right]\right\}$$

(8) $$\mu_{ij} \equiv \frac{\partial w_i}{\partial \ln p_j} = \gamma_{ij} - \mu_i\left(\alpha_j + \sum_k \gamma_{jk} \ln P_k\right) - \frac{\lambda_i \beta_j}{b(p)}\left\{\ln\left[\frac{m}{a(p)}\right]\right\}^2$$

The budget elasticities are then given by $e_i = \mu_i / w_i + 1$. With a positive β and a negative λ, for example as suggested for clothing and alcohol in Lewbel's empirical study (1997), the budget elasticities will appear to be larger than unity at low levels of expenditure, ultimately becoming less than unity as the total expenditure increases and the term in λ_i becomes more important and dominates. Such commodities thereby have the features of luxuries at low levels of total expenditure and necessities at high levels.

The uncompensated price elasticities are given by $e_{ij}^{u} = \mu_{ij} / w_i - \delta_{ij}$, where δ_{ij} is the Kronecker delta. The Slutsky equation, $e_{ij}^{c} = e_{ij}^{u} + e_i w_j$, can be used to calculate the set of compensated elasticities e_{ij}^{c} and to assess the symmetry and negativity conditions by examining the matrix with elements $w_i[e_{ij}^{c}]$, which should be symmetric and negative semidefinite in the usual way.

The QUAIDS model identified by (6) exhibits flexibility in the representation of income effects, being of rank three. It has the same degree of price flexibility as the usual linear AIDS and translog models. It also has the linear AIDS model nested within it as a special case while having as few additional parameters over the AIDS model as possible.

Additivity, homogeneity and symmetry define exact linear restrictions on the parameters of the QUAIDS share equations implied by the utility maximization objective. Referring to the notation in equation (6) they are expressed as

(9) $$\sum_i \alpha_i = 1; \ \sum_i \gamma_{ij} = 0; \ \sum_i \beta_i = 0, \ \sum_i \lambda_i = 0$$

(10) $$\sum_j \gamma_{ij} = 0,$$

(11) $$\gamma_{ij} = \gamma_{ji} \quad \forall i \neq j,$$

respectively. Provided that equations (9), (10), and (11) hold, the estimated demand functions add up to the total expenditure (9), are homogenous of degree zero in prices and income (10), and satisfy Slutsky symmetry (11).

Wahl and Hayes (1990) estimated the LAIDS model nested in the QAIDS identified above using Japanese expenditure and price data from 1965 to 1986 relating to five different meat groups: Wagyu beef, import quality beef, pork, chicken and fish.

These meat groups are denoted by i = 1, 2, 3, 4, 5, respectively, with the AIDS model nested as a special case. The empirical analysis in this paper updates Wahl and Hayes' line of analysis with the data set now spanning the years 1965 to 1999, and expands the model to the more flexible Quadratic AIDS to allow for more general Engel curves. Because the meat expenditure shares (w_i) sum to one, the covariance matrix for the meat demand system composed of all five individual expenditure share equations is singular. One of the equations is dropped to make the system equations estimable, and afterwards the dropped equation parameters can be estimated by exploiting their functional dependence on the other parameters of the system. In this analysis, the fish share equation was deleted and the parameters for this equation were eventually recovered via symmetry, homogeneity and adding up constraints as expressed in (9)-(11).

5. Data Description

The expenditure and price data for the 1965-1999 period were assembled from a variety of yearbooks including *Statistical Yearbook, Monthly Statistics of Agriculture, Forestry and Fisheries, Meat Statistics in Japan,* and reports published by the Japanese ministry of Agriculture, Forestry, and Fisheries. The expenditure and retail prices for pork, chicken and fish meat are from the *Annual Report on the Family Income and Expenditure Survey*. Retail fish prices, from the same data resource, are calculated as averages of fresh and salted fish prices weighted by the proportional consumption levels of each fish type, and the expenditure on fish naturally is the expenditures on fresh and salted fish combined. Retail Wagyu and dairy beef prices are calculated by multiplying the respective wholesale prices by a markup coefficient of 2.1156, where the data source for these wholesale prices is *Statistics of Meat Marketing and Meat Statistics in Japan*.

Additionally, since the QUAIDS model employed here only serves conceptually as a demand subsystem of a larger structural market model with endogenous prices, the endogeneity of the explanatory variables was accommodated by a GMM estimation framework based on instrumental variables, which consisted of ten principal components capturing 99.8% of the variability in a set of variables that included macroeconomic variables such as the consumer, wholesale, and producer price indexes; monthly family income; population; the average number of household members; the U.S. consumer price index; birth rates for Wagyu cattle, dairy cattle, and hogs; slaughter weights; farm price of milk; and the wholesale unit value of corn.

6. Estimation Methodology

The choice of the parameter α_0 followed the original discussion in Deaton and Muellbauer (1980) and was chosen to be just below the lowest value of *ln(m)* in our data. Let θ represent the remaining unknown parameters of the model, and represent the nonlinear share equation in stylized form as

(12) $$w_i = g_i(x_i, \theta_i) + \varepsilon_i, i = 1, 2, \cdots, 5$$

where x_i represents all right hand side endogenous variables including prices and expenditure for the *ith* share equation, and θ_i denotes the model parameters for the i^{th} share equation.

Rewrite (12) in vertically stacked form as

(13) $$w_v = g_v(x, \theta) + \varepsilon_v$$

where $w_v = \begin{pmatrix} w_1 \\ \vdots \\ w_5 \end{pmatrix}$, $\varepsilon_v = \begin{pmatrix} \varepsilon_1 \\ \vdots \\ \varepsilon_5 \end{pmatrix}$, $x = \begin{pmatrix} 1 & \ln(p) & \ln(m) \end{pmatrix}$, $g_v(x,\theta) = \begin{bmatrix} g_1(x,\theta_1) \\ \vdots \\ g_5(x,\theta_5) \end{bmatrix}$, and $\theta = \begin{pmatrix} \theta_1 \\ \vdots \\ \theta_5 \end{pmatrix}$

where

(14) $$\theta_i = \left(\alpha_i, \gamma_{i1}, ..., \gamma_{i5}, \beta_i, \lambda_i\right)', \; i = 1, 2, \cdots, 5,$$

(15) $$g_i(x,\theta_i) = \left(1_n \;\middle|\; \ln\left(\text{p}\right) \;\middle|\; \frac{m}{a(\text{p})} \;\middle|\; \frac{1}{b(\text{p})}\left\{\ln\left[\frac{m}{a(\text{p})}\right]\right\}^2 \right)\theta_i, \; i = 1, 2, \cdots, 5,$$

In order to estimate (13), the GMM procedure is utilized, which provides a very general framework in which the usual estimating equation information may be biased, or the system of equations may over-determine the unknown parameters of interest. Three different variants of the GMM method were used to estimate the Japanese meat demand system, based on assumptions about the covariance structure and whether restrictions were imposed on the model parameters: (i) $\text{cov}(u) = \Sigma = \sigma^2 I$, (ii) $\text{cov}(u) = \Sigma \neq \sigma^2 I$, and (iii) $\text{cov}(u\ ) = \Sigma \neq \sigma^2 I$ and linear restrictions (9) – (11) imposed.

In the case of GMM estimation of model with $\text{cov}(u) = \Sigma = \sigma^2 I$, when the number of estimation equations was greater than the number of parameters, Hansen (1982) indicated the most efficient estimator of the model parameters is

(16) $$\hat{\theta}\left(I_5\right) = \arg\min_{\theta}\left[\left(w_v - g_v(x,\theta)\right)'\left(I_5 \otimes Z(Z'Z)^{-1}Z'\right)\left(w_v - g_v(x,\theta)\right)\right].$$

We note that this estimator is equivalent to two-stage nonlinear least squares applied to each equation separately.

Asymptotically,

(17) $$\hat{\theta}\left(I_5\right) \sim N\left(\theta, \sigma^2 \left\{ \frac{\partial g_v}{\partial \theta}\bigg|_{\hat{\theta}} \left[I_5 \otimes Z(Z'Z)^{-1}Z' \right] \frac{\partial g_v}{\partial \theta}'\bigg|_{\hat{\theta}} \right\}^{-1}\right)$$

where $\sigma^2 = \left[\left(w_v - g_v(x,\hat{\theta}(I_5))\right)'\left(w_v - g_v(x,\hat{\theta}(I_5))\right)\right]/(5n)$ and $\frac{\partial g_v}{\partial \theta}\Big|_{\hat{\theta}}$ is a $(k \times 5n)$ matrix of derivatives of the n observations on the systematic parts of the 5 share equations with respect to all $k=40$ parameters of the system, evaluated at $\hat{\theta}$.

Similarly, in the case of GMM estimation with non-spherical disturbances $\text{cov}(u) = \Sigma \neq \sigma^2 I$, the asymptotically efficient estimator of the model parameters is given by

(18) $$\hat{\theta}\left(\hat{\Sigma}\right) = \arg\min_{\theta}\left[\left(w_v - g_v(x,\theta)\right)'\left(\hat{\Sigma}^{-1} \otimes Z(Z'Z)^{-1}Z'\right)\left(w_v - g_v(x,\theta)\right)\right].$$

where $\hat{\Sigma} = \sum_{j=1}^{n} \hat{\varepsilon}_h\left[j,.\right]' \hat{\varepsilon}_h\left[j,.\right]' / n$, with $\hat{\varepsilon}_h$ denoting the $(n \times 5)$ horizontally concatenated (by equation) estimates of the model residuals based on the estimator obtained from solving (16). This GMM estimator accounts for the possibility of a generalized contemporaneous covariance structure for the noise term by choosing an appropriate weight matrix. Asymptotically,

(19) $$\hat{\theta}\left(\hat{\Sigma}\right) \sim N\left(\theta, \left\{ \frac{\partial g_v}{\partial \theta}\bigg|_{\hat{\theta}} \left[\hat{\Sigma}^{-1} \otimes Z(Z'Z)^{-1}Z' \right] \frac{\partial g_v'}{\partial \theta}\bigg|_{\hat{\theta}} \right\}^{-1}\right)$$

In the case of linear restrictions (9) – (11) directly imposed on the estimation of the system of equations, let the restrictions be rewritten as

(20) $r = R\theta$

The estimation followed two sequential steps: first the restricted nonlinear share equations were estimated with an identity weight matrix in the GMM quadratic objective function, and then residuals were subsequently calculated to provide a restricted covariance matrix taking into considerations homogeneity and symmetry; secondly, identity matrix was replaced by the restricted covariance matrix as the weight matrix in the second step objective function to re-estimate the restricted nonlinear share equations. This sequential estimation resembles the sequence of nonlinear 2SLS followed by nonlinear GLS estimation, except that the restricted nonlinear QUAIDS model dropped the fish share equation, and homogeneity and symmetry were imposed throughout each iteration of nonlinear optimization procedure. The procedure yields consistent estimates of the model parameters.

Regarding the variance-covariance matrix in the restricted case, reconsider the restricted nonlinear share equation systems estimation subject to homogeneity and symmetry. The nonlinear estimation problem with the fish share equation dropped can be written as:

(21) $$s_n(\theta) = \min\left[\left(w_s - g_s(x,\theta)\right)'\left(\hat{\Sigma}^{-1} \otimes Z(Z'Z)^{-1}Z'\right)\left(w_s - g_s(x,\theta)\right)\right]$$

(22) $$\text{s.t. } \mathrm{r} - \mathrm{R}\theta = 0$$

where $w_s = \begin{pmatrix} w_1 \\ \vdots \\ w_4 \end{pmatrix}$, $x = \begin{pmatrix} 1 & \ln(p) & \ln(m) \end{pmatrix}$, $g_s(x,\theta) = \begin{bmatrix} g_1(x,\theta_1) \\ \vdots \\ g_4(x,\theta_5) \end{bmatrix}$, and $\theta = \begin{pmatrix} \theta_1 \\ \vdots \\ \theta_4 \end{pmatrix}$.

Let λ_n be the Lagrange multiplier for the minimization of $s_n(\theta)$ subject to $\mathrm{r} - \mathrm{R}\theta = 0$, and let

(23) $$\Phi = \left[\frac{\partial g_s}{\partial \theta} \bigg|_{\hat{\theta}} \left(\hat{\Sigma}_s^{-1} \otimes Z(Z'Z)^{-1} Z' \right) \frac{\partial g_s'}{\partial \theta} \bigg|_{\hat{\theta}} \right]^{-1}$$

with $\hat{\Sigma}_s^{-1}$ resulting from the estimation of the restricted nonlinear QAIDS model with the identity matrix as the weight matrix in the GMM quadratic objective function.

The variance-covariance matrix is then

(24) $$\Phi_r = \Phi - \Phi R'\left(R\Phi R'\right)^{-1} R\Phi$$

Asymptotic standard errors for the demand elasticities can be calculated based on the delta method for approximating standard errors relating to nonlinear functions of parameters.

The optimization of the quadratic GMM nonlinear objective functions utilized a second-order Taylor series expansion for the local approximation in each updating iteration until convergence, and was based on the Newton Algorithm in the Constrained Optimization package distributed by Aptech Systems in the GAUSS programming language.. Therefore, analytical gradient and Hessian matrices were provided to ensure optimum performance of the optimization algorithm, providing 16 decimal accuracy of analytical gradients and Hessians. The use of analytical derivatives to machine precision should help stabilize nonlinear model estimation and effectively shorten convergence time and the number of iterations required for convergence. The analytical gradient and Hessian matrix are described ahead.

Consider the quadratic objective function defined in (16), and differentiate with respect to the θ vector to obtain

(25) $$\frac{\partial[\cdot]}{\partial \theta} = -2 \frac{\partial g_V(x,\theta)}{\partial \theta} \left(I_5 \otimes Z(Z'Z)^{-1} Z' \right) \left(w_V - g_V(x,\theta) \right)$$

This is now a 40 by 1 vector, and embedded within the expression defining this vector, we have the derivative matrix $\frac{\partial g_V(x,\theta)}{\partial \theta}$, which is a 40 by 175 matrix representing 40 derivatives (with respect to the parameters) evaluated at 175 different sample observation points (there were 35 sample observations per equation utilized in the current study). Another way of representing this function definition, which facilitates computations as well as the derivation of the Hessian, is:

(26) $$\frac{\partial[\cdot]}{\partial\theta} = -2\left[\sum_{i=1}^{n}\left(\frac{\partial g_V(x_i,\theta)}{\partial\theta}\otimes Z[i,.]\right)\right]\left(I_5 \otimes (Z'Z)^{-1} Z'\right)(w_v - g_v(x,\theta))$$

where $\frac{\partial g_V(x_i,\theta)}{\partial \theta}$ denotes the (40×5) derivative evaluated at the i[th] sample point.

Let Υ be defined as a *horizontal concatenation* of 40 of the following 40 by 1 vectors:

(27) $$\Upsilon_j \equiv -2\sum_{i=1}^{n}\left(\frac{\partial g_V(x_i,\theta)}{\partial\theta'\partial\theta_j}\otimes Z[i,.]\right)\left(I_5\otimes(Z'Z)^{-1}Z'\right)(w_v - g_v(x,\theta)),\ \text{j = 1, ... , 40.}$$

Then the full Hessian is given by:

(28) $$\frac{\partial^2[\cdot]}{\partial\theta\,\partial\theta'} = 2\frac{\partial g_V(x,\theta)}{\partial\theta}\left(I_5\otimes(Z'Z)^{-1}Z'\right)\frac{\partial g_V(x,\theta)}{\partial\theta'} + \Upsilon$$

For evidently the first time in an empirical application, bootstrapping was used in this highly nonlinear modeling environment to estimate variability in demand model parameter estimates and associated demand elasticities. It also illustrated the utility of using bootstrapping, as opposed to relying only on derivative based asymptotic approximations, for assessing the reliability of estimated results. With bootstrap resampling size equal 1000, the iterative bootstrapping procedure can be described as:

1. Row-wise draw a random sample of size n (the number of observations), with replacement, from the original data matrix of shares, right hand side explanatory variables, and instrumental variables. These random draws of size n constitute a new bootstrap data set sample.
2. Repeat the nonlinear estimation procedure stated above to generate a new set of bootstrapped model parameter estimates.
3. Redo step 1 to 2 listed in this setting for 1000 times.
4. Based on the 1000 estimated demand elasticities (or other function) based on the parameters, calculate the standard errors of the elasticities (or other functions) using standard sample moment-based estimators.

Unlike the general nonparametric bootstrap technique starting with random draws of residuals, this bootstrap procedure excludes the possibility of obtaining budget shares greater than 1 or less than 0 that would be possible after adding randomly drawn residuals obtained from nonlinear QUAIDS estimation. Instead, this row-wise bootstrapping randomly draws n observations on shares, prices, expenditures and instrumental variables simultaneously, preserving the consistency of the observations on shares, prices, expenditures and instrumental variables between the original data set and the bootstrapped data sample, respecting key features (bounded shares, and adding up of shares) of the true data generating process.

7. Estimation Results

The estimated intercept, price, and expenditure parameters obtained from the Japanese meat demand system using the GMM, unrestricted GLS GMM, and the Restricted GLS GMM are presented in Table 1 to 4 respectively, along with standard errors corresponding to the parameters. Table 5 to 8 presents the bootstrap estimation results.

The interpretation of the parameter estimates themselves is less intuitive than interpreting elasticities implied by them. However, in the way of comparison between the various parameter estimation results, at least two general patterns stand out. First of all, the unrestricted GMM and unrestricted GLS GMM are notably more similar in magnitude and signs compared to the restricted GLS GMM results. Secondly, the restricted GLS GMM estimates are notably more precise than the unrestricted ones. Note that for the restricted GLS GMM method, the standard errors reported for this method are significantly smaller than those for the unrestricted GMM and GLS methods. This result was in fact expected given that the restricted GLS GMM is more efficient by incorporating both the heteroskedasticity and linear restrictions of the QUAIDS model arising from microeconomic theory.

The compensated and uncompensated price elasticity estimates implied by the three estimation methods were presented in Table 2, 3 for classical nonlinear GMM and 6, 7 for nonparametric bootstrapping estimation. The formulae used to calculate these elasticities are from Banks, Blundell and Lewbel (1997). The direct price elasticities are indicated in the table in bold font. All of the direct price elasticities calculated by either GLS GMM method have the correct signs, and the magnitudes of the elasticities appear to be plausible. More ideally, for either GLS GMM methods, the import quality beef price elasticity, which is quality comparable to beef quality in the United Sates, appears to be lower, being in the inelastic range, compared to those for Wagyu beef. This was consistent with expectations since the direct price elasticities for the Japanese native breed beef should be higher than that of the import quality beef, given the high priced, luxury good nature of the commodity. Additionally, the compensated direct price elasticities for the other three types of meat - pork, chicken and fish - have the right sign for all three GMM methods. The magnitude of the price elasticity was reasonable given the fact that pork, chicken and fish are very popular and are also relatively easily substitutable commodities.

The budget elasticities implied by the three estimation methods are presented in Table 4 and 8. The expenditure elasticity on Wagyu beef was positive and had the largest magnitude, based on the Restricted GLS GMM estimating method. Of the remaining expenditure elasticities, the elasticities for import quality beef, chicken, and fish were very similar in magnitude across the two unrestricted GMM methods.

Viewing the empirical results holistically across all commodities, across direct price and expenditure elasticities, and in terms of the precision of the information associated with the empirical results, it would appear that the restricted GLS GMM methodology provides arguably the most *a priori* defensible and useful results.

Comparing standard errors for demand elasticities based on bootstrapping techniques and asymptotic approximations, we found bootstrapping estimation provided generally somewhat larger standard errors. This may not be surprising given that asymptotic approximations are based on large sample sizes, and given that the sample size used in this study was only 35.

8. Conclusions

The empirical results are economically meaningful across all commodities under three GMM estimation methods, GMM, GLS GMM and Restricted GLS GMM. However, the neoclassically restricted GLS GMM methodology provides arguably the most *a priori* defensible and useful results, both in terms of economic interpretability, and statistical reliability.

The application of nonparametric Bootstrapping techniques to the Restricted GLS GMM is computer intensive. However, the method is tractable, and it provides an alternative approach for assessing the variability of the true data generating process underlying the highly nonlinear QAIDS model, as well as the variability of highly nonlinear functions of the estimated parameters of such models. This application provides a substantive illustration of the utility of using Bootstrapping for assessing the reliability of estimated results compared to asymptotic approximations.

Comparing to previous studies relating to Japanese meat demand that employed the more restrictive linear or nonlinear AIDS model, the paper illustrates the substantially increased flexibility of the QUAIDS model of consumer demand, providing more meaningful and a priori defensible results, including in particular the ability to more flexibly represent income effects on consumption.

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Appendix:

Table 1. Parameter Estimates for the Japanese Meat Demand System

		GMM		GLS GMM		Restricted GLS GMM	
Share		Estimate	Std.Error	Estimate	Std.Error	Estimate	Std.Error
Wagyu Beef	α_1	0.0674	0.1466	0.2754	0.2536	-0.1106	0.0470
	γ_{11}	-0.8561	0.3353	-1.2036	0.4452	-0.1224	0.0369
	γ_{12}	0.0695	0.2453	0.1040	0.2812	0.0236	0.0278
	γ_{13}	0.6663	0.2264	0.9978	0.2307	0.1968	0.0349
	γ_{14}	0.1376	0.0965	0.3515	0.1387	0.0825	0.0149
	γ_{15}	-0.2411	0.1064	-0.2363	0.1239	-0.1805	0.0342
	β_1	1.0767	0.2113	1.3057	0.2751	0.3823	0.0523
	λ_1	-1.0543	0.3762	-1.6386	0.7925	-0.1581	0.0450
IQBeef	α_2	0.1057	0.0866	0.0990	0.0953	0.2730	0.0553
	γ_{21}	0.0913	0.2436	0.1181	0.2805	0.0236	0.0278
	γ_{22}	-0.0239	0.0755	-0.0184	0.0765	-0.0696	0.0232
	γ_{23}	-0.1509	0.1718	-0.1962	0.2136	-0.0938	0.0296
	γ_{24}	-0.0670	0.0570	-0.0817	0.0768	-0.0497	0.0162
	γ_{25}	0.1465	0.0693	0.1459	0.0546	0.1895	0.0364
	β_2	-0.1548	0.2861	-0.1714	0.2882	-0.2380	0.0764
	λ_2	0.2277	0.3276	0.2903	0.4428	0.1309	0.0410
Pork	α_3	0.0576	0.0956	-0.0975	0.1541	0.3361	0.0561
	γ_{31}	0.5173	0.1624	0.8868	0.2247	0.1968	0.0349
	γ_{32}	-0.0150	0.1110	-0.0619	0.1702	-0.0938	0.0296
	γ_{33}	-0.1842	0.2533	-0.5054	0.3152	-0.1012	0.0772
	γ_{34}	-0.1087	0.0791	-0.2748	0.1263	-0.1460	0.0242
	γ_{35}	-0.0448	0.1030	-0.0094	0.1295	0.1443	0.0413
	β_3	-0.5376	0.2189	-0.8609	0.2201	-0.5823	0.0836
	λ_3	0.4744	0.2361	1.0528	0.3839	0.3323	0.0490
Chicken	α_4	0.0594	0.0427	-0.0109	0.0702	0.2860	0.0491
	γ_{41}	0.2085	0.0732	0.3829	0.0960	0.0825	0.0149
	γ_{42}	0.0016	0.0460	-0.0210	0.0742	-0.0497	0.0162
	γ_{43}	0.0674	0.1466	0.2754	0.2536	-0.1460	0.0242
	γ_{44}	-0.8561	0.3353	-1.2036	0.4452	-0.0443	0.0152
	γ_{45}	0.0695	0.2453	0.1040	0.2812	0.1576	0.0335
	β_4	0.6663	0.2264	0.9978	0.2307	-0.4036	0.0650
	λ_4	0.1376	0.0965	0.3515	0.1387	0.2175	0.0354
Fish	α_5	-0.2411	0.1064	-0.2363	0.1239	0.2154	0.0459
	γ_{51}	1.0767	0.2113	1.3057	0.2751	-0.1805	0.0342
	γ_{52}	-1.0543	0.3762	-1.6386	0.7925	0.1895	0.0364
	γ_{53}	0.1057	0.0866	0.0990	0.0953	0.1443	0.0413
	γ_{54}	0.0913	0.2436	0.1181	0.2805	0.1576	0.0335
	γ_{55}	-0.0239	0.0755	-0.0184	0.0765	-0.3108	0.0202
	β_5	-0.1509	0.1718	-0.1962	0.2136	0.8416	0.0446
		-0.0670	0.0570	-0.0817	0.0768	-0.5226	0.0227

Table 2. Compensated Price Elasticities for the Japanese Meat Demand System

	GMM		GLS GMM		Restricted GLS GMM	
	Estimate	**Std.Error**	**Estimate**	**Std.Error**	**Estimate**	**Std.Error**
Wagyu beef - Wagyu beef	**-1.3797**	1.2082	**-1.7285**	1.2769	**-1.4006**	0.4493
IQ beef	-0.5400	0.6331	-0.5175	0.6741	-0.2609	0.2685
Pork	3.5660	1.6602	3.4157	1.6335	1.1410	0.2769
Chicken	-0.3685	1.0077	0.3251	1.1115	0.0266	0.2270
Fish	0.0018	0.5931	-0.0046	0.5834	0.4938	0.1954
IQ beef - Wagyu beef	-0.1392	0.5913	-0.2094	0.5695	-0.1817	0.1945
IQ beef	**-0.9300**	0.4150	**-0.8624**	0.3978	**-1.2666**	0.1527
Pork	-0.7706	0.8373	-0.7979	0.6816	0.0114	0.1363
Chicken	-0.3541	0.5843	-0.2986	0.5042	0.1201	0.1038
Fish	1.7091	0.2779	1.7285	0.2693	1.3169	0.1089
Pork - Wagyu beef	0.6782	0.3804	0.8442	0.4064	0.5149	0.1263
IQ beef	0.3442	0.2612	0.3168	0.2553	0.0055	0.0866
Pork	**-0.6863**	0.5985	**-0.8732**	0.6131	**-0.3178**	0.1604
Chicken	-0.0375	0.3569	-0.2322	0.3636	-0.0068	0.1235
Fish	-0.2723	0.1978	-0.2293	0.1880	-0.1958	0.0592
Chicken - Wagyu beef	0.4867	0.3548	0.6485	0.3777	0.0405	0.2030
IQ beef	0.3948	0.2459	0.3678	0.2392	0.1475	0.1301
Pork	-0.0815	0.5471	-0.2845	0.5636	-0.0073	0.2456
Chicken	**-0.6210**	0.3366	**-0.7993**	0.3433	**-0.3673**	0.2204
Fish	-0.0526	0.1860	-0.0088	0.1764	0.1866	0.0995
Fish - Wagyu beef	-0.0734	0.0633	-0.0915	0.0632	0.0572	0.0259
IQ beef	0.0574	0.0394	0.0723	0.0400	0.2421	0.0203
Pork	0.0885	0.0986	0.0392	0.0950	-0.0565	0.0179
Chicken	0.1593	0.0602	0.1970	0.0567	0.0315	0.0169
Fish	**-0.2608**	0.0312	**-0.2514**	0.0309	**-0.2743**	0.0243

Table 3. Uncompensated Price Elasticities for the Japanese Meat Demand System

	GMM		GLS GMM		Restricted GLS GMM	
	Estimate	Std.Error	Estimate	Std.Error	Estimate	Std.Error
Wagyu beef - Wagyu beef	**-1.4584**	1.2235	**-1.7864**	1.3008	**-1.5595**	0.4556
IQ beef	-0.6476	0.6486	-0.5966	0.7104	-0.4781	0.2929
Pork	3.3865	1.6313	3.2837	1.5632	0.7786	0.2411
Chicken	-0.4567	1.0329	0.2603	1.1401	-0.1513	0.2304
Fish	-0.5884	0.6504	-0.4384	0.7306	-0.6976	0.3754
IQ beef - Wagyu beef	-0.2709	0.5697	-0.3308	0.5515	-0.2640	0.2015
IQ beef	**-1.1101**	0.4711	**-1.0284**	0.4477	**-1.3792**	0.1843
Pork	-1.0710	0.8454	-1.0749	0.6971	-0.1764	0.1264
Chicken	-0.5016	0.6311	-0.4347	0.5487	0.0278	0.1028
Fish	0.7215	0.5096	0.8178	0.4660	0.6994	0.3377
Pork - Wagyu beef	0.6268	0.3764	0.7735	0.4094	0.4194	0.1266
IQ beef	0.2739	0.2807	0.2201	0.2771	-0.1250	0.1011
Pork	**-0.8036**	0.5916	**-1.0345**	0.5808	**-0.5356**	0.1437
Chicken	-0.0950	0.3775	-0.3114	0.3813	-0.1137	0.1307
Fish	-0.6578	0.2727	-0.7595	0.2751	-0.9118	0.1625
Chicken - Wagyu beef	0.4435	0.3503	0.5860	0.3799	-0.0416	0.2028
IQ beef	0.3356	0.2633	0.2824	0.2569	0.0353	0.1444
Pork	-0.1802	0.5449	-0.4271	0.5360	-0.1945	0.2362
Chicken	**-0.6695**	0.3554	**-0.8693**	0.3590	**-0.4592**	0.2256
Fish	-0.3772	0.2516	-0.4775	0.2483	-0.4288	0.2238
Fish - Wagyu beef	-0.1460	0.0629	-0.1629	0.0628	0.0014	0.0272
IQ beef	-0.0420	0.0428	-0.0253	0.0432	0.1657	0.0278
Pork	-0.0773	0.0973	-0.1236	0.0936	-0.1839	0.0308
Chicken	0.0779	0.0635	0.1171	0.0599	-0.0311	0.0228
Fish	**-0.8058**	0.0439	**-0.7865**	0.0429	**-0.6931**	0.0926

Table 4. Budget Elasticities for the Japanese Meat Demand System

	GMM		GLS GMM		Restricted GLS GMM	
	Budget Elasticity	**Standard error**	**Budget Elasticity**	**Standard error**	**Budget Elasticity**	**Standard error**
Wagyu beef	1.0444	0.8366	0.7676	1.0582	2.1080	0.5491
IQ beef	1.7474	0.8463	1.6113	0.7936	1.0924	0.5506
Pork	0.6822	0.4013	0.9380	0.3837	1.2667	0.2460
Chicken	0.5742	0.3750	0.8293	0.3350	1.0888	0.3292
Fish	0.9643	0.0667	0.9468	0.0643	0.7410	0.1581

Table 5. Parameter Estimates for the Japanese Meat Demand System

	Restricted GLS GMM				
		Classical GMM		Nonparametric Bootstrap	
	Estimate	Std. Errors	T Values	Std. Errors	T Values
Share	-0.1106	0.0470	-2.3526	0.0889	-1.2437
Wagyu Beef	-0.1224	0.0369	-3.3181	0.1539	-0.7952
γ_{11}	0.0236	0.0278	0.8490	0.0815	0.2897
γ_{12}	0.1968	0.0349	5.6427	0.1033	1.9044
γ_{13}	0.0825	0.0149	5.5352	0.0595	1.3869
γ_{14}	-0.1805	0.0342	-5.2851	0.0621	-2.9072
γ_{15}	0.3823	0.0523	7.3053	0.1800	2.1245
β_1	-0.1581	0.0450	-3.5094	0.3127	-0.5054
λ_1	0.2730	0.0553	4.9323	0.0842	3.2424
IQBeef	0.0236	0.0278	0.8490	0.0815	0.2897
γ_{21}	-0.0696	0.0232	-2.9946	0.0820	-0.8493
γ_{22}	-0.0938	0.0296	-3.1648	0.0528	-1.7772
γ_{23}	-0.0497	0.0162	-3.0725	0.0338	-1.4697
γ_{24}	0.1895	0.0364	5.2064	0.0630	3.0070
γ_{25}	-0.2380	0.0764	-3.1159	0.1548	-1.5377
β_2	0.1309	0.0410	3.1943	0.0947	1.3824
λ_2	0.3361	0.0561	5.9967	0.0918	3.6610
Pork	0.1968	0.0349	5.6427	0.1033	1.9044
γ_{31}	-0.0938	0.0296	-3.1648	0.0528	-1.7772
γ_{32}	-0.1012	0.0772	-1.3113	0.0907	-1.1162
γ_{33}	-0.1460	0.0242	-6.0466	0.0388	-3.7617
γ_{34}	0.1443	0.0413	3.4928	0.0649	2.2231
γ_{35}	-0.5823	0.0836	-6.9675	0.0911	-6.3882
β_3	0.3323	0.0490	6.7816	0.1343	2.4741
λ_3	0.2860	0.0491	5.8299	0.0681	4.1998
Chicken	0.0825	0.0149	5.5352	0.0595	1.3869
γ_{41}	-0.0497	0.0162	-3.0725	0.0338	-1.4697
γ_{42}	-0.1460	0.0242	-6.0466	0.0388	-3.7617
γ_{43}	-0.0443	0.0152	-2.9085	0.0285	-1.5549
γ_{44}	0.1576	0.0335	4.7090	0.0468	3.3689
γ_{45}	-0.4036	0.0650	-6.2135	0.0841	-4.7993
β_4	0.2175	0.0354	6.1461	0.1645	1.3216
λ_4	0.2154	0.0459	4.6880	0.1512	1.4244
Fish	-0.1805	0.0342	-5.2851	0.0621	-2.9072
γ_{51}	0.1895	0.0364	5.2064	0.0630	3.0070
γ_{52}	0.1443	0.0413	3.4928	0.0649	2.2231
γ_{53}	0.1576	0.0335	4.7090	0.0468	3.3689
γ_{54}	-0.3108	0.0202	-15.4161	0.1142	-2.7204
γ_{55}	0.8416	0.0446	18.8558	0.2157	3.9021
	-0.5226	0.0227	-23.0666	0.0643	-8.1233

λ_5	-0.1106	0.0470	-2.3526	0.0889	-1.2437

Table 6. Compensated Price Elasticities for the Japanese Meat Demand System

	Restrict GLS GMM				
		Classical GMM		Nonparametric Bootstrap	
	Estimate	Std.Error	T Values	Std.Error	T Values
Wagyu beef - Wagyu beef	**-1.4006**	0.4493	-3.1171	0.5936	-2.3596
IQ beef	-0.2609	0.2685	-0.9718	0.3854	-0.6770
Pork	1.1410	0.2769	4.1213	0.3634	3.1396
Chicken	0.0266	0.2270	0.1173	0.2516	0.1058
Fish	0.4938	0.1954	2.5276	0.2572	1.9199
IQ beef - Wagyu beef	-0.1817	0.1945	-0.9345	0.2740	-0.6631
IQ beef	**-1.2666**	0.1527	-8.2930	0.2657	-4.7671
Pork	0.0114	0.1363	0.0836	0.2012	0.0567
Chicken	0.1201	0.1038	1.1567	0.1371	0.8760
Fish	1.3169	0.1089	12.0908	0.1574	8.3689
Pork - Wagyu beef	0.5149	0.1263	4.0775	0.1674	3.0758
IQ beef	0.0055	0.0866	0.0639	0.1273	0.0434
Pork	**-0.3178**	0.1604	-1.9819	0.1808	-1.7576
Chicken	-0.0068	0.1235	-0.0547	0.1208	-0.0559
Fish	-0.1958	0.0592	-3.3075	0.1029	-1.9032
Chicken - Wagyu beef	0.0405	0.2030	0.1993	0.2322	0.1743
IQ beef	0.1475	0.1301	1.1336	0.1728	0.8534
Pork	-0.0073	0.2456	-0.0296	0.2355	-0.0309
Chicken	**-0.3673**	0.2204	-1.6665	0.1647	-2.2296
Fish	0.1866	0.0995	1.8753	0.1235	1.5112
Fish - Wagyu beef	0.0572	0.0259	2.2063	0.0369	1.5514
IQ beef	0.2421	0.0203	11.9447	0.0285	8.4827
Pork	-0.0565	0.0179	-3.1616	0.0325	-1.7372
Chicken	0.0315	0.0169	1.8671	0.0215	1.4617
Fish	**-0.2743**	0.0243	-11.2767	0.0477	-5.7545

Table7. Uncompensated Price Elasticities for the Japanese Meat Demand System

		Restrict GLS GMM			
		Classical GMM		Nonparametric Bootstrap	
	Estimate	Std.Error	T Values	Std.Error	T Values
Wagyu beef - Wagyu beef	**-1.5595**	0.4556	-3.4226	0.6086	-2.5623
IQ beef	-0.4781	0.2929	-1.6325	0.4364	-1.0957
Pork	0.7786	0.2411	3.2292	0.2783	2.7978
Chicken	-0.1513	0.2304	-0.6569	0.2514	-0.6020
Fish	-0.6976	0.3754	-1.8583	0.5797	-1.2033
IQ beef - Wagyu beef	-0.2640	0.2015	-1.3106	0.2792	-0.9456
IQ beef	**-1.3792**	0.1843	-7.4847	0.3088	-4.4660
Pork	-0.1764	0.1264	-1.3956	0.1637	-1.0777
Chicken	0.0278	0.1028	0.2709	0.1334	0.2088
Fish	0.6994	0.3377	2.0712	0.4536	1.5421
Pork - Wagyu beef	0.4194	0.1266	3.3120	0.1754	2.3906
IQ beef	-0.1250	0.1011	-1.2370	0.1512	-0.8269
Pork	**-0.5356**	0.1437	-3.7265	0.1474	-3.6349
Chicken	-0.1137	0.1307	-0.8697	0.1270	-0.8948
Fish	-0.9118	0.1625	-5.6098	0.2204	-4.1375
Chicken - Wagyu beef	-0.0416	0.2028	-0.2052	0.2319	-0.1793
IQ beef	0.0353	0.1444	0.2445	0.2005	0.1760
Pork	-0.1945	0.2362	-0.8236	0.2062	-0.9432
Chicken	**-0.4592**	0.2256	-2.0352	0.1695	-2.7094
Fish	-0.4288	0.2238	-1.9161	0.2852	-1.5032
Fish - Wagyu beef	0.0014	0.0272	0.0507	0.0370	0.0372
IQ beef	0.1657	0.0278	5.9540	0.0346	4.7861
Pork	-0.1839	0.0308	-5.9746	0.0414	-4.4456
Chicken	-0.0311	0.0228	-1.3605	0.0255	-1.2210
Fish	**-0.6931**	0.0926	-7.4814	0.0818	-8.4707

Table 8. Budget Elasticities for the Japanese Meat Demand System

		Restricted GLS GMM			
		Classical GMM		Nonparametric Bootstrap	
	Budget Elasticity	**Standard error**	**T Values**	**Standard error**	**T Values**
Wagyu beef	2.1080	0.5491	3.8390	0.8947	2.3560
IQ beef	1.0924	0.5506	1.9839	0.7199	1.5175
Pork	1.2667	0.2460	5.1498	0.3520	3.5987
Chicken	1.0888	0.3292	3.3076	0.4032	2.7000
Fish	0.7410	0.1581	4.6881	0.1332	5.5625