

Estimating the Market Demand for Value-Added Beef: Testing for BSE Announcement Effects Using a Nested PIGLOG Model Approach

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Steven S. Vickner¹, DeeVon Bailey² and Al Dustin³

¹ Corresponding Author:

Associate Professor, Department of Economics, Utah State University,
Room 612, Eccles Business Building, 3530 Old Main Hill, Logan, UT, 84322-3530,
Phone: 435-797-2963, Fax: 435-797-2701, Email: svickner@econ.usu.edu

² Professor, Department of Economics, Utah State University,
Room 606, Eccles Business Building, 3530 Old Main Hill, Logan, UT, 84322-3530,
Phone: 435-797-2316, Fax: 435-797-2701, Email: dbailey@econ.usu.edu

³ Head, Department of Farm & Ranch Management, Bridgerland Applied Technology
College, 1301 North 600 West, Logan, UT, 84321,
Phone: 435-753-6780, Fax: 435-752-2016, Email: adustin@bridgerlandatc.org

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Literature Review

To analyze the market demand for fresh retail meats in the grocery store distribution channel, we build upon a well-developed microeconomic model of consumer choice that incorporates the role information plays in individual decision-making (Swartz and Strand; Smith, van Ravenswaay and Thompson; Brown and Schrader; Wessells, Miller and Brooks; Piggott; Piggott and Marsh; Kalaitzandonakes, Marks and Vickner; Marks, Kalaitzandonakes and Vickner). Mathios (2000) in particular investigated the impact of labels on a processed food market using a random utility model. Teisl, Bockstael and Levy (2001) used the Foster and Just (1989) framework in conjunction with an Almost Ideal Demand System (Deaton and Muelbauer) to investigate the impact of labeling in a small sample of stores in New England. Both the Mathios and Teisl et al. studies were limited in terms of data quality; lack of a representative sample and low frequency time series diminished their findings.

Objectives, Data, Procedures and Methods

The principal empirical objective of this part of the project is to determine how price changes of fresh pork, chicken and seafood affect the demand for fresh beef products in the grocery store distribution channel. Substitution effects, if present, would serve to diminish the feasibility of a Utah's Own beef product. For example, if substitution effects were present, a price cut in fresh pork or chicken would lead to an inward or leftward shift in the demand for fresh beef, hence limiting the volume of beef sales and associated revenues.

Using detailed, representative point-of-purchase scanner data graciously supplied by Salt Lake City based Associated Food Stores, Inc. we estimate a state-of-the-art demand system. The 79MB of weekly data spanned the weeks beginning May 9, 2004 to May 1, 2005 for twenty of

the stores they own. The data was aggregated by store and UPC code into a useable weekly data set to investigate the retail demand for only fresh beef, pork, chicken and seafood. The twenty stores were spatially dispersed throughout their Utah selling region and well-represent the major population centers in the state. Within this time frame, three separate USDA-APHIS announcements (i.e., on June 25, 2004, June 29, 2004 and November 18, 2004) were made regarding the testing of BSE in the domestic beef cattle herd. This non-price, non-income information may be vital in influencing purchasing patterns for fresh meats and thus will be included in this part of the study.

The empirical demand system stems from a well-developed microeconomic model of consumer choice. Let x_i be the quantity consumed of retail fresh meat product i , where $i = 1, \dots, n$. Then \mathbf{x} is a $n \times 1$ vector with elements x_i . Further, let q_i be the elements of the $n \times 1$ vector \mathbf{q} , where q_i is the perceived quality of good x_i . Perceived product quality may be influenced by a myriad of non-price, non-income factors including, but not limited to, product labels, the media, food safety recalls, advertising, and brand image. Let s_i represent a non-price, non-income information index characterizing the quality of meat product i such that $\frac{\partial q_i}{\partial s_i} < 0$; higher levels of bad news leads to a lower level of perceived quality. More generally, we let $\mathbf{q}(\mathbf{s})$.

As is the case for most applied demand studies, data is typically unavailable to construct a complete demand system (Varian). Thus, we assume the consumer's utility function is weakly separable between retail fresh meats and all other goods. In our problem, the individual consumer chooses \mathbf{x} to maximize

$$U(\mathbf{x}, \mathbf{q}) \tag{1}$$

subject to the linear budget constraint

$$\mathbf{p}' \mathbf{x} = M \quad (2)$$

where $U(\cdot)$ is the utility function, \mathbf{p}' is a $1 \times n$ vector of prices of retail fresh meats, and M is total expenditure for retail fresh meats.

The solution to the consumer's problem results in a vector of n Marshallian or uncompensated demand functions

$$\mathbf{x}^m(\mathbf{p}, M, \mathbf{q}) \quad (3)$$

with the usual properties. Because $\mathbf{q}(\mathbf{s})$, we may express the Marshallian demand functions as

$$\mathbf{x}^m(\mathbf{p}, M, \mathbf{s}) \quad (4)$$

so that the Marshallian demands now include a vector of shift parameters based on the information index and other shifters like seasonality.

Substituting (4) into the utility function $U(\cdot)$, we obtain the indirect utility function $V(\mathbf{p}, M, \mathbf{s})$. Others in the literature (i.e., Teisl, Roe and Hicks, equation (3), p. 344) begin their model development with essentially this expression for the indirect utility function. Inverting the indirect utility function, we obtain the consumer's expenditure function

$$E(\mathbf{p}, u, \mathbf{s}). \quad (5)$$

By applying Shephard's lemma to the expenditure function

$$\frac{\partial E(\mathbf{p}, u, \mathbf{s})}{\partial \mathbf{p}} = \mathbf{x}^h(\mathbf{p}, u, \mathbf{s}) \quad (6)$$

we obtain the n Hicksian demand functions and express them in expenditure share form in the $n \times 1$ vector \mathbf{w} . The presence of the informational shift variables \mathbf{s} in (6) presents a knotty problem when estimating \mathbf{w} .

We represent \mathbf{w} using the corrected Linear Approximate Almost Ideal Demand System (LA-AIDS) model (Deaton and Muelbauer; Moschini). This is a special case of the nested PIGLOG model (Piggott). The expenditure share (w_i) for the i^{th} processed food product, is given by

$$w_i = \alpha_i + \sum_{j=1}^n \gamma_{ij} \ln p_j + \beta_i \ln \left(\frac{M}{P} \right) \quad (7)$$

where the usual unobservable, nonlinear AIDS price index is replaced by the loglinear analog of the Laspeyres price index for constant base period shares w^o (Moschini). It is given by

$$\ln(P) = \sum_{i=1}^n w_i^o \ln(p_i). \quad (8)$$

The informational shift variables are incorporated into the α_i parameters as

$$\alpha_i = \phi_i + \theta_{1i}(\text{Seasonality1}) + \theta_{2i}(\text{Seasonality2}) + \kappa_{1i}(\text{BSE1}) + \kappa_{2i}(\text{BSE2}) + \kappa_{3i}(\text{BSE3}). \quad (9)$$

For the singular, conditional LA-AIDS model, the adding up conditions are given by

$$\sum_{i=1}^n \phi_i = 1, \quad \sum_{i=1}^n \theta_{1i} = 0, \quad \sum_{i=1}^n \theta_{2i} = 0, \quad \sum_{i=1}^n \kappa_{1i} = 0, \quad \sum_{i=1}^n \kappa_{2i} = 0, \quad \sum_{i=1}^n \kappa_{3i} = 0, \quad \sum_{i=1}^n \gamma_{ij} = 0 \quad \forall j, \quad (10)$$

and $\sum_{i=1}^n \beta_i = 0$.

Homogeneity and symmetry are, respectfully, imposed on the model with

$$\sum_{j=1}^n \gamma_{ij} = 0 \quad \forall i \quad \text{and} \quad \gamma_{ij} = \gamma_{ji} \quad \forall i \neq j. \quad (11)$$

The use of translating and scaling techniques have long been used to incorporate shift variables such as demographics into singular expenditure systems without violating Closure Under Unit Scaling or CUUS (Pollak and Wales; Lewbel). The notion of CUUS is maintained when the estimated parameters, such as the usual α , γ , and β parameters in the Almost Ideal

Demand System (Deaton and Muelbauer), do not depend on the data's scaling, especially the scaling of the data related to the shift variables themselves (Alston, Chalfant, and Piggott; Piggott; Piggott and Marsh).

Econometric Estimation and Autocorrelation Correction

Following Berndt and Savin, with appropriate substitutions and addition of subscripts representing weekly time periods, the demand model of retail fresh meats given by (7) may be rewritten more compactly as

$$\mathbf{w}_t = \mathbf{\Pi} \mathbf{z}_t + \mathbf{v}_t \quad (12)$$

where \mathbf{w}_t is a $n \times 1$ vector of conditional expenditure shares of fresh meats, $\mathbf{\Pi}$ is a $n \times K$ matrix of unknown parameters, \mathbf{z}_t is $K \times 1$ vector of explanatory variables, \mathbf{v}_t is a $n \times 1$ vector of stochastic disturbances governed by the following process

$$\mathbf{v}_t = \mathbf{R} \mathbf{v}_{t-1} + \boldsymbol{\varepsilon}_t \quad (13)$$

for time $t = 2, \dots, T$, \mathbf{R} is a $n \times n$ matrix of unknown parameters and $\boldsymbol{\varepsilon}_t$ is a $n \times 1$ vector of residuals. Further it is assumed $\{\boldsymbol{\varepsilon}_t\}$ is distributed $iid N(\mathbf{0}, \boldsymbol{\Sigma})$ for $t = 2, \dots, T$.

Let $\mathbf{1}'$ be a $1 \times n$ vector of ones. Because the demand model of retail fresh meats is singular (i.e., its shares sum to one), $\mathbf{1}' \mathbf{w}_t = 1$ for $t = 1, \dots, T$. The adding up conditions also imply $\mathbf{1}' \mathbf{\Pi} = [1 \ 0 \ 0 \ \dots \ 0]$, $\mathbf{1}' \mathbf{v}_t = 0$ for $t = 1, \dots, T$ and, since \mathbf{v}_{t-1} and $\boldsymbol{\varepsilon}_t$ are independent, $\mathbf{1}' \mathbf{R} = k'$. The final result indicates the n column sums of \mathbf{R} equal the same constant.

The autocorrelation correction procedure for singular equation systems as developed by Berndt and Savin is quite flexible and subsumes several interesting special cases. When the $n \times n$ elements of matrix \mathbf{R} are set to zero, this represents the case of no autocorrelation such that

$\mathbf{v}_t = \boldsymbol{\varepsilon}_t$ and $\mathbf{w}_t = \mathbf{\Pi}\mathbf{z}_t + \boldsymbol{\varepsilon}_t$. For the present data set this assumption is implausible and, hence, introduces an omitted variable bias in the matrix of parameter estimates $\mathbf{\Pi}$. If the n elements on the diagonal of matrix \mathbf{R} are restricted to be the same constant and the off-diagonal elements are restricted to all be zeros, this single parameter estimate for serial correlation correction will equal k' since $\mathbf{1}'\mathbf{R} = k'$. This parsimonious assumption is maintained for the present study. It is noted \mathbf{R} may be kept in its most general form with n^2 unique elements. For the present study, the full matrix over-parameterizes the model.

In our empirical application, consider the case where we have four fresh retail meat products ordered as follows: fresh beef, fresh pork, fresh chicken and fresh seafood. This results in $n = 4$ conditional expenditure share equations. Since the system is singular as the shares sum to one, the 4th equation is dropped from the estimation. Equations (12) and (13), with the 4th equation dropped may be rewritten as

$$\mathbf{w}_t^4 = \mathbf{\Pi}_4\mathbf{z}_t + \mathbf{v}_t^4 \quad (14)$$

and

$$\mathbf{v}_t^4 = \mathbf{R}_4\mathbf{v}_{t-1}^4 + \boldsymbol{\varepsilon}_t^4 \quad (15)$$

for $t = 2, \dots, T$. Since \mathbf{R}_4 is now a 3×4 , equations (14) and (15) are not estimable. Recognizing $\mathbf{1}'\mathbf{v}_t = 0$, this is remedied (Berndt and Savin) by the following transformation

$$\bar{\mathbf{R}}_4 = \begin{bmatrix} (R_{11} - R_{14}) & (R_{12} - R_{14}) & (R_{13} - R_{14}) \\ (R_{21} - R_{24}) & (R_{22} - R_{24}) & (R_{23} - R_{24}) \\ (R_{31} - R_{34}) & (R_{32} - R_{34}) & (R_{33} - R_{34}) \end{bmatrix}$$

so that $\bar{\mathbf{R}}_4$ is now a 3×3 . Now the $n - 1$ column sums in $\bar{\mathbf{R}}_4$ each equal zero. Substituting $\bar{\mathbf{R}}_4$ into (15) we obtain

$$\mathbf{v}_t^4 = \bar{\mathbf{R}}_4\mathbf{v}_{t-1}^4 + \boldsymbol{\varepsilon}_t^4 \quad (16)$$

Further substituting (16) into (14), we obtain the estimable, theoretically consistent, conditional nested PIGLOG model of retail meats as given by

$$\mathbf{w}_t^4 = \bar{\mathbf{R}}_4 \mathbf{w}_{t-1}^4 + \mathbf{\Pi}_4 \mathbf{z}_t - \bar{\mathbf{R}}_4 \mathbf{\Pi}_4 \mathbf{z}_{t-1} + \boldsymbol{\varepsilon}_t^4 \quad (17)$$

for $t = 2, \dots, T$. Using PROC MODEL routine in the SAS ETS module, we jointly estimate the parameters in $\mathbf{\Pi}_4$ and $\bar{\mathbf{R}}_4$ using nonlinear seemingly unrelated regressions (SUR) (Gallant). An iterated seemingly unrelated regressions approach was not used due to lack of stability in the likelihood ratio tests for non-price, non-income informational shifters. However, it should be noted the iterated SUR and SUR led to very similar parameter estimates and levels of statistical significance with the former being only slightly more efficient. This model is highly nonlinear since $\mathbf{\Pi}_4$ and $\bar{\mathbf{R}}_4$ enter into (17) as a product. It is noted $\{\boldsymbol{\varepsilon}_t\}$ is distributed $iid N(\mathbf{0}, \boldsymbol{\Sigma})$ for $t = 2, \dots, T$ (Berndt and Savin; Gallant). Finally, $\bar{\mathbf{R}}_4$ is given in its diagonal form for first-order autocorrelation correction. The parameter estimates for $\mathbf{\Pi}_4$ and $\bar{\mathbf{R}}_4$ are reported and discussed in the Empirical Results section.

Hypothesis Testing of Consumer Response to Information

Germane to this study is the cross-equation hypothesis test in which the three equations manifested in (17) are estimated with (9) versus the restricted model where (9) is replaced with

$$\alpha_i = \phi_i + \theta_{1i}(\textit{Seasonality1}) + \theta_{2i}(\textit{Seasonality2}) \quad (18)$$

for $i = 1, \dots, 3$ such that $\kappa_{11} = \kappa_{12} = \kappa_{13} = \kappa_{21} = \kappa_{22} = \kappa_{23} = \kappa_{31} = \kappa_{32} = \kappa_{33} = 0$. The restricted model imposes the null hypothesis that the BSE announcements have no impact on the aggregate consumer behavior in the market for retail fresh meats. This test is considered to be far superior to a simple inspection of the parameter by parameter asymptotic t -statistics, especially in small

samples. Using any single-equation approach, it is not possible to comprehensively test the BSE announcement effects on the demand system overall. Gallant outlines a procedure to test this cross-equation restriction using a likelihood ratio test. The likelihood ratio statistic for our model is given by

$$LR = S(\hat{\pi}_R, \hat{\Sigma}_U) - S(\hat{\pi}_U, \hat{\Sigma}_U) \quad (19)$$

where $S(\cdot)$ is the objective function of the SUR multiplied by the number of time periods net of any lags, $S(\hat{\pi}_R, \hat{\Sigma}_U)$ is $S(\cdot)$ for the estimated restricted model where the covariance matrix is held constant from the estimated unrestricted model, and $S(\hat{\pi}_U, \hat{\Sigma}_U)$ is $S(\cdot)$ for the unrestricted model. The test statistic is distributed asymptotically chi-square with $(K^U - K^R)$ degrees of freedom where K^U is the number of estimated parameters in the unrestricted model and K^R be the number of estimated parameters in the restricted model. If LR is less than the chi-square critical value for some alpha level of significance then we fail to reject the null hypothesis and conclude the restricted and unrestricted models are statistically no different. The outcome of the hypothesis tests would quantify whether or not the BSE announcements affected the demand for the fresh meat products.

Empirical Results

A table of descriptive statistics for the continuous variables in the conditional demand model of fresh retail meats is given in Table 1. The parameter estimates of the conditional demand model of retail fresh meats may be found in Table 2. Table 3 summarizes the likelihood ratio tests of the BSE announcements. Table 4 contains the estimated Marshallian and Hicksian price elasticities and the conditional expenditure elasticities.

The unrestricted conditional demand system outlined in Table 2 exhibits reasonable properties for the given data set and application. Four of the six price parameters, two of the three conditional expenditure parameters and all three intercepts are statistically significant ($p < 0.10$). As for non-price and non-expenditure shifters, four of the six seasonality parameters and none of the nine BSE announcement parameters are statistically significant ($p < 0.10$). The Durbin Watson statistics indicate the parsimonious version of the Berndt-Savin autocorrelation correction procedure is successful in purging serial correlation from the model. While the adjusted R^2 appear somewhat lower than desired, it is emphasized the shares are extremely volatile at the weekly level in a small sample of stores for a given region so the levels of this diagnostic are not unexpected. Moreover, data regarding other shifters such as features and displays were unavailable from our data supplier. Stability or robustness of the parameter estimates, significance of the parameter estimates and stability of the likelihood ratio tests are quite impressive for this model, hence outweighing the importance of the adjusted R^2 values.

In Table 3, we see when we impose the null hypothesis of no BSE announcement effect (i.e., $\kappa_{11} = \kappa_{12} = \kappa_{13} = \kappa_{21} = \kappa_{22} = \kappa_{23} = \kappa_{31} = \kappa_{32} = \kappa_{33} = 0$), we find no statistical difference between the unrestricted and restricted models at the 1, 5 and 10 percent levels of significance (only the 10 percent level is reported). This test is considered to be far superior to a simple inspection of the parameter by parameter asymptotic t -statistics, especially in small samples. Using any single-equation approach, it is not possible to comprehensively test the BSE announcement effects on the demand system overall. We can conclude for this data set and application, the BSE announcements collectively had no impact on consumer response.

Finally, perhaps most important to this feasibility study is the estimation of price elasticities. Alston, Foster and Green outline functional forms of LA-AIDS elasticities and we

use them here. The uncompensated or Marshallian own and cross price elasticities exhibit reasonable direction and magnitude with the only exception being the cross price effect of pork in the beef equation (i.e., indicating complementarity); own price elasticities are negative and all cross price elasticities but one are positive. The Hicksian elasticities too are quite reasonable and similar too. The conditional expenditure elasticities each show the rates of segment growth as the fresh meat category expenditures rise; beef and pork rise proportionally slower, while chicken and seafood rise proportionally faster.

In every case except for the one mentioned cross price effects indicate a substitution relationship between fresh retail beef and other fresh retail meats. In terms of the feasibility of a Utah's Own beef product, we must be aware that fresh retail beef sales do not occur in a vacuum in the grocery store distribution channel. The merchandising strategies for fresh retail pork, chicken and seafood do indeed impact quantity demanded of fresh retail beef products. Any feasibility study must account for such effects or the projections of demand and, hence revenue, of fresh retail beef products will be necessarily overstated.

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Table 1. Descriptive Statistics of Selected Demand System Variables¹

	Mean	Standard Deviation	Minimum	Maximum
Expenditure Shares				
<i>Beef</i>	0.5827	0.0513	0.4065	0.6601
<i>Pork</i>	0.1424	0.0362	0.0920	0.2890
<i>Chicken</i>	0.2236	0.0605	0.1566	0.4783
<i>Seafood</i>	0.0513	0.0162	0.0232	0.1027
Prices ²				
<i>Beef</i>	1.7005	0.3037	0.6444	2.0603
<i>Pork</i>	1.5624	0.0590	1.4318	1.6796
<i>Chicken</i>	2.3452	0.3104	1.5207	2.9294
<i>Seafood</i>	2.6628	0.3657	2.0183	3.2721

¹ Based on 52 consecutive weekly observations. ² All products in US dollars per pound.

Table 2. Conditional LA-AIDS Model Parameter Estimates¹

	<i>Beef</i>	<i>Pork</i>	<i>Chicken</i>
Prices (γ)			
<i>Beef</i>	-0.0675** (0.0284) ²	-0.0128 (0.0250)	0.0677** (0.0299)
<i>Pork</i>		-0.1945*** (0.1042)	0.0260 (0.0316)
<i>Chicken</i>			-0.1141** (0.0437)
Expenditure (β)	-0.0854** (0.0386)	-0.0252 (0.0287)	0.1068** (0.0452)
Intercept (ϕ)	0.3700* (0.0928)	0.1518** (0.0645)	0.5230* (0.1120)
Seasonality1 (θ_1)	-0.0968** (0.0437)	0.1365* (0.0299)	-0.0400 (0.0540)
Seasonality2 (θ_2)	-0.1077** (0.0441)	0.0163 (0.0283)	0.0943*** (0.0544)
BSE1 (κ_1)	-0.0003 (0.0455)	0.0434 (0.0307)	-0.0602 (0.0560)
BSE2 (κ_2)	0.0351 (0.0450)	0.0093 (0.0292)	-0.0289 (0.0555)
BSE3 (κ_3)	-0.0133 (0.0437)	0.0034 (0.0282)	0.0163 (0.0539)
Autocorrelation ³ (ρ)	0.2503** (0.1002)	0.2503** (0.1002)	0.2503** (0.1002)
Durbin Watson	1.8435	2.3560	2.2230
Adjusted R^2	0.2571	0.3073	0.1673
Log Likelihood	53.7386		

¹ Symmetry and homogeneity are imposed on the model. ² Standard error in parentheses.

³ Results are corrected for first-order autocorrelation using the diagonal $\bar{\mathbf{R}}_4$ matrix (Berndt and Savin).

Note: *, ** and *** denote statistical significance at the 0.01, 0.05 and 0.10 levels respectively.

Table 3. Likelihood Ratio Test for BSE Announcement Effects¹

$$H_0: \kappa_{11} = \kappa_{12} = \kappa_{13} = \kappa_{21} = \kappa_{22} = \kappa_{23} = \kappa_{31} = \kappa_{32} = \kappa_{33} = 0$$

LR statistic = 4.4199

$$\chi_{\alpha=0.10} = 14.6837$$

$$K^U = 28$$

$$K^R = 19$$

$$M = 3$$

$$T = 51$$

¹ The likelihood ratio (LR) statistic is defined to be $LR = S(\hat{\pi}_R, \hat{\Sigma}_U) - S(\hat{\pi}_U, \hat{\Sigma}_U)$ where the restricted (R) and unrestricted (U) values are so indicated, K represents number of estimated parameters, M represents number of equations and T represents time periods net of lags (Gallant).

Table 4. Estimated Price and Expenditure Elasticities

	<i>Beef</i>	<i>Pork</i>	<i>Chicken</i>	<i>Seafood</i>
Uncompensated				
<i>Beef</i>	-1.0305	-0.0011	0.1490	0.0291
<i>Pork</i>	0.0130	-2.3402	0.2218	1.2820
<i>Chicken</i>	0.0244	0.0480	-1.6172	0.0670
<i>Seafood</i>	0.2039	3.5260	0.3829	-5.1846
Compensated				
<i>Beef</i>	-0.5332	0.1205	0.3398	0.0729
<i>Pork</i>	0.4928	-2.2230	0.4059	1.3243
<i>Chicken</i>	0.8855	0.2585	-1.2868	0.1427
<i>Seafood</i>	0.8284	3.6787	0.6226	-5.1297
Expenditure	0.8535	0.8234	1.4778	1.0719

The uncompensated price elasticities are defined by $E_{ij} = -\delta + \left(\frac{\gamma_{ij}}{w_i}\right) - \left(\frac{\beta_i}{w_i}\right)w_j$

where γ and β are defined above, expenditure shares are taken at their sample means, and δ is the Kronecker delta (Alston, Foster and Green). The conditional expenditure elasticity ($E_{i,x}$) is given by $E_{i,x} = 1 + \frac{\beta_i}{w_i}$. Compensated elasticities are recovered using the Slutsky formula in elasticity form.