Multidimensional Evaluation of Flexible Functional Forms for Production Analysis

Fermin S. Ornelas and C. Richard Shumway*

Abstract

Several common flexible functional forms are evaluated for Texas agricultural production utilizing three procedures. Nested hypothesis tests indicate that the normalized quadratic is the marginally-preferred functional form followed by the generalized Leontief. Predictive accuracy results are ambiguous between the generalized Leontief and the normalized quadratic. Statistical performance favors the normalized quadratic. These two functional forms consistently dominate the translog.

Key words: Box-Cox, functional form, prediction, production, statistical performance

Texas has traditionally been a major producer of vegetables. In 1970 it supplied 9.2 percent of the value of fresh vegetables and 7.0 percent of all vegetables produced in the U.S. and ranked third among states in value of both fresh and total vegetable production. However, in the last two decades Texas vegetable output has declined in both real and nominal terms. While the top producing state of California increased its nominal value of production 285 percent for fresh vegetables and 302 percent for all vegetables, Texas decreased by 13 percent and 3 percent, respectively. Texas currently ranks sixth among the 50 states in value of fresh vegetables, ninth in value of all vegetables produced, and produces less than 3 percent of the value of either category (USDA).

With the ultimate objective of determining why Texas has experienced such a large relative decline in vegetable production, this paper reports preliminary work aimed at designing an appropriate model of vegetable supply. It focuses specifically on functional form selection. Because vegetables in Texas are frequently produced on farms that also produce other commercial agricultural commodities and because the aggregate agricultural resources in the state can be used to produce many commodities, the economic model is couched within the context of multiple-output production.

In empirical work, economic theory frequently provides guidance regarding the set of variables to be included in an econometric model. Economic relationships among these variables, parameter signs, and even magnitudes of estimated parameters are often hypothesized based on theoretical expectations. However, economic science is less precise on the choice of functional form, leaving econometric practitioners to their own creativity in this aspect of model specification. To fill this vacuum, researchers have advocated alternative procedures to guide selection of a

---

*Fermin Ornelas is an econometrician for American Express, Phoenix, AZ, and formerly a research assistant at Texas A&M University. C. Richard Shumway is a professor of agricultural economics at Texas A&M.

Appreciation is extended to Robert Evenson, Chris McIntosh, and their associates for access to the extensive state-level data they compiled and to Teo Ozuna, Carl Shafer, Steve Fuller, and Ray Battalio for constructive comments on earlier drafts of the manuscript.

Texas Agricultural Experiment Station Technical Article No. 30565.

J. Agr. and Applied Econ. 25 (2), December, 1993: 106-118

functional form. Parametric and nonparametric techniques, Bayesian analysis, nonnested hypothesis testing, predictive evaluation, and theoretical/statistical performance have been proposed in the literature as means for functional form selection (Griffin et al.; Thompson; Dutta).

Numerous studies of agricultural production have employed only a single, arbitrarily chosen functional form (e.g., Ball; Shumway and Alexander; Lopez). Model design is often based on previous applications of a given functional specification. Nested testing of alternative functional forms for production, cost, and profit function studies has been conducted infrequently (Appelbaum; Berndt and Khaled; Chalfant; Ornelas et al.). Predictive performance (McIntosh, 1990) and sensitivity of important statistical and theoretical results among alternative functional forms (Swamy and Binswanger; Guilkey et al.; Villezca; Baffes and Vasavada) can also be utilized to evaluate model specifications.

Three evaluative techniques are implemented in this paper in a sequential fashion to select functional form for an econometric model of Texas agricultural production. Box-Cox nested hypothesis testing, out-of-sample predictive accuracy comparisons, and theoretical/statistical performance are used to guide the investigator in choosing among alternative locally-flexible functional forms of a restricted (or variable) profit function. Regardless of findings, this multidimensional evaluation will carry an important analytical benefit. If the test results consistently identify one preferred functional form, the analyst will have a strong basis for choosing it. If the results are not consistent, he/she will be cautioned about assigning too high a preference to any one alternative.

The translog (TL), normalized quadratic (NQ), generalized Leontief (GL), and square-rooted quadratic (SRQ) functional forms are examined by means of nested hypothesis testing using the generalized Box-Cox specification and highly aggregated data.[1] The forecasting performance of the first three nested functional forms, which are frequently used for production analysis, is also compared. Finally, the preferred functional forms based on these two criteria are applied to less aggregated data, and the statistical and theoretical performance of their estimates is examined.

In the sequenced tests, successively fewer alternatives were considered in each test. The reason for the above order was simplicity. The Box-Cox tests were conducted first because estimation of this functional form with restrictions on the power parameters can be accomplished by iterative OLS using a bi-dimensional grid search. All four of the noted specifications can be nested within the Box-Cox specification when the power parameters are restricted to alternative values. Systems estimation of supply functions for predictive purposes can be accomplished with valid asymptotic properties without maintaining nonlinear inequality restrictions (Jorgenson and Lau). However, nonlinear inequality restrictions are required when economic theory is fully incorporated into model design. While maintaining such restrictions complicates the estimation, theoretical consistency is easily tested when all restrictions of the theory (including the nonlinear inequalities) can be maintained in one of the models. While this ordering simplified our task, it may have also impacted our conclusions since the number of alternatives tested was not constant.

The Model

The state was modeled as though it were a price-taking, profit-maximizing firm with a state-level production (transformation) function describing the conversion of a variety of inputs into a variety of agricultural outputs.[2] Assuming the underlying state-level production technology is a well-defined, twice-continuously-differentiable, concave function with one or more inputs fixed in the short run, a flexible approximation of the dual restricted profit function can be defined as the generalized quadratic Box-Cox model (QBCM):

$$\pi(\delta) = \alpha_0 + \alpha' X(\lambda) + .5X(\lambda)'\beta X(\lambda) + \varepsilon, \tag{1}$$

where X is a column vector of output and variable input normalized prices, fixed input quantities, and other non-price exogenous variables; π is the level of normalized profits; δ and λ are power transformations; α_0, α, and β are conformable parameters (scalar, vector, and matrix, respectively) to be estimated; and ε is a column vector of random error terms. Profit and prices are normalized by an output or variable input price, or a linear combination of them, which maintains linear homogeneity of the profit function in exogenous prices regardless of functional form. Using Appelbaum's notation, the specifications $\pi(\delta)$ and $X(\lambda)$ represent the following transformations:

$$
\begin{array}{lrcll}
(2) & \pi(\delta) & = & (\pi^{2\delta} - 1)/2\delta & \text{if} \quad \delta \neq 0, \\
 & & = & \ln\pi & \text{if} \quad \delta = 0, \\
 & X(\lambda) & = & (X^{\lambda} - 1)/\lambda & \text{if} \quad \lambda \neq 0, \\
 & & = & \ln X & \text{if} \quad \lambda = 0.
\end{array}
$$

Under the appropriate parametric restrictions for the power transformations, the QBCM nests three commonly employed locally-flexible functional forms (TL, NQ, GL), as well as the SRQ. By utilizing l'Hopital's rule, the power transformations are continuous around zero. Therefore, at δ=0 and λ=0 the QBCM becomes the TL functional form:

$$(3) \qquad \ln\pi = \alpha_0 + \alpha'\ln X + .5\ln X'\beta\ln X + \varepsilon_1.$$

When $\delta=\lambda=.5$ the QBCM becomes the GL functional form:

$$(4) \qquad \pi = b_0 + 2b'X^{.5} + (X^{.5})'BX^{5} + \varepsilon_2.$$

At δ=.5 and λ=1 it is the NQ functional form:

$$(5) \qquad \pi = c_0 + c'X + .5X'CX + \varepsilon_3.$$

At $\delta=\lambda=1$ it is the SRQ functional form:

$$(6) \qquad \pi = [d_0 + 2d'X + X'DX]^{.5} + \varepsilon_4,$$

where b_0, c_0, d_0, b, c, d, B, C, and D are conformable parameters.

Application of Hotelling's lemma to expressions (3), (4), (5), and (6) renders a system of linear output and input share equations for (3), and linear output supply and input demand equations for (4), (5), and (6). Thus, without loss of generality, one can express the following as a general expression for the system of NQ first-derivative equations:

$$(7) \qquad Y = a + AX + e,$$

where $Y = (y_1,...,y_n)$ is a vector of netput quantities (y_i>0 for outputs, y_i<0 for inputs), a and A are parameters, A is a symmetric matrix, and e is a vector of error terms. Equation (7) can also define the TL first-derivative equations with y_i redefined as s_i and X redefined as ln$X$, where s_i represents netput i's receipt (or negative expenditure) as a share of profit. For the SRQ equations, y_i is the quantity of netput i multiplied by profit. And,

$$(8) \qquad y_i = b_i/x_i^{.5} + B_i(X/x_i)^{5} + e_i, \quad i=1, ..., n,$$

for the generalized Leontief first-derivative equations, where b_i and B_i are parameters, and B_i is the i^th^ row of a symmetric matrix. Each of these sets of first derivatives are frequently estimated as a system of equations with iterative SUR. Theoretical properties such as linear homogeneity and symmetry are generally imposed, while monotonicity and convexity can be tested or checked. Monotonicity and convexity require nonlinear programming techniques when they are maintained in estimation.

Data and Variable Specification

To prepare the data necessary for empirical analysis, we used the livestock, field and fruit crop quantity and price series compiled by Robert Evenson at Yale University, Chris McIntosh at the University of Georgia, and their associates. Annual state-level data used from their series for Texas from 1951 to 1986 included fourteen field crops, four fruit crops, and seven livestock commodities. Residual crop and livestock categories included other commercial food and fiber products.

Prices and quantities for the six vegetables employed in this analysis were collected from *Texas Vegetable Statistics* (Texas Dept. of Agriculture). These data were collected for two reasons: (a) not all major vegetables were included in the Evenson-McIntosh series, and (b) the same source for all vegetable prices was desired. Pesticide quantities and prices were assembled by Chris

McGath at the Economic Research Service. March-April average temperature and annual precipitation data weighted by cropland harvested were from Teigen and Singer. These weather variables were chosen based on empirical work by Villezca. Government policy data on maximum and minimum effective support prices and effective diversion payment for each farm program were compiled by McIntosh (1989). A simple average of the maximum and minimum values of these variables was employed in the specification of our policy variables -- effective support prices and effective diversion payments (Houck and Ryan). The data used in this paper are available on request from the junior author.

Based on Lim's nonparametric tests, expected prices for non-government-supported commodities were specified as one-year lagged prices.[3] For government-supported commodities (barley, corn, cotton, oats, peanuts, rice, sorghum, soybeans, and wheat), we used Romain's expected price specification which was a weighted average of anticipated market (one-year lagged) price and effective support price. McIntosh (1990) found that this specification gave lower out-of-sample forecast errors than either of two alternatives. The weight was based on the relative magnitudes of the anticipated market price and effective support price.

To reduce collinearity problems and computational burden when performing the nested Box-Cox tests and examining predictive performance, the data were aggregated as noted in table 1. They included three output categories (vegetables, other crops, and livestock), one variable input category, and a fixed input category. Although these aggregates are a little different, they are largely consistent with categories for which Lim and Shumway failed to reject separability by nonparametric testing. All output and variable input price aggregates and fixed input quantity aggregates were computed utilizing the Tornqvist Index (an exact index for a linear homogeneous translog functional form).

The set of response variables for Box-Cox testing and predictive accuracy comparison included three output and one variable input categories. The set of independent variables included expected prices of the response variables, quantity of the aggregate fixed input, and time. This last variable was included as a proxy for disembodied technical change.

To allow for greater disaggregation when pursuing the theoretical/statistical performance objective, four output categories were created as noted in table 1: government-supported crops, vegetables, other non-supported crops, and livestock. Variable inputs were divided into three categories: materials, pesticides, and hired labor-capital.

Thus, the response variables specified when examining theoretical/statistical performance included vegetables (cabbage, cantaloupes, carrots, onions, potatoes, and watermelons), other non-supported crops, livestock, materials, and pesticides. The set of independent variables included expected prices for the response variables normalized by the hired labor-capital price, quantity of government-supported crops, a fixed input aggregate, aggregate effective diversion payments, rain, temperature, and time. Aggregate effective diversion payments were computed as an arithmetic index using value shares as weights. The only regressors transformed in alternative functional form specifications were the price variables. Including quantity of government-supported crops as a regressor in this model followed the logic of Moschini's supply-management model.

Estimation Methods

To conduct Box-Cox testing, the quadratic generalized Box-Cox was estimated with iterative OLS using a bi-dimensional grid search (Greene, p. 344) for the power transformations (δ, λ). The restricted cases required that δ and λ be equal to zero for the translog, .5 for the GL, 1.0 for the SRQ, and .5 and 1.0, respectively, for the NQ. Thus, the QBCM was estimated at these restricted power parameter values and at their unrestricted values that maximized the log-likelihood function for equation (1). Linear homogeneity was maintained in each case.

To estimate systems of equations specified in (7) and (8) for the predictive accuracy and theoretical/statistical performance comparisons, the stochastic version of the model was specified as follows

Table 1. Output and Input Aggregations

Aggregated Model Category	Disaggregated Model Category	Commodities or Inputs in Category
1. Vegetables	1. Vegetables	Cabbage, Cantaloupes, Carrots, Onions, Potatoes, Watermelons
2. Other Crops	2a. Government-Supported Crops	Barley, Corn, Cotton, Oats, Peanuts, Rice, Sorghum, Soybeans, Wheat
	2b. Non-Supported Crops	Grapefruit, Hay, Oranges, Other Crops (Field, Vegetable, and Fruit)
3. Livestock	3. Livestock	Broilers, Cattle and Calves Eggs, Hogs, Milk, Sheep and Lambs, Turkeys, Other Livestock
4. Variable Inputs	4a. Materials	Feed, Fertilizer, Seed, Miscellaneous Inputs
	4b. Pesticides	Pesticides
	4c. Hired Labor-Capital	Capital Services, Hired Labor, Machinery Operating Inputs
5. Fixed Inputs	5. Fixed Inputs	Family Labor, Land

$$(9) \qquad Y_t = f(X_t, \theta) + \zeta_t, \qquad t = 1, \ldots, T,$$

where Y_t is a vector of output supplies and input demands, X is a matrix of exogenous prices, diversion payment, and other exogenous variables, T is the number of observations, and θ is a vector of parameters to be estimated. The stochastic error term, ζ, was assumed to be normal and independently and identically distributed with mean zero and a constant variance-covariance matrix, Ω. The iterative version of Zellner's seemingly unrelated regression was employed to estimate the equation system specified in (9).[4]

In addition to linear homogeneity, symmetry restrictions on the cross-price parameters were maintained in the predictive accuracy comparison. To examine theoretical/statistical performance, the output supply and input demand equations were estimated maintaining linear homogeneity, symmetry, and convexity. Convexity was maintained by the Cholesky factorization (Lau). The covariance matrix for the seemingly unrelated system subject to homogeneity and symmetry restrictions was obtained by iterative SUR. The stabilized covariance matrix[5] was then maintained, and nonlinear generalized least squares estimates of the parameters were obtained subject also to the convexity conditions. The nonlinear programming approach of Talpaz et al. was employed for this objective using MINOS version 5.1.

Empirical Results

Nested Hypothesis Tests

The statistical results of the Box-Cox nested hypothesis tests are presented in table 2. The power parameter values for the unrestricted Box-Cox were δ=.5 and λ=2.01. At a .05 significance level, neither the NQ nor the GL functional form was rejected. The preferred choice was the NQ function. Both the TL and SRQ functional forms were rejected.

Our rejection of the TL and nonrejection of the NQ was consistent with the recent findings of nested functional form tests for a restricted profit function specification of U.S. agriculture (Ornelas et al.). Our rejection of the SRQ and nonrejection of the GL, however, was opposite to the Ornelas et al. findings. Our failure to reject either the GL or NQ

Table 2. Log-Likelihood Results

Locally-Flexible Functional Form	Transformation (δ,λ)	Log-Likelihood Function Value	Likelihood Ratio Test[a]
Quadratic Generalized Box Cox	(.5, 2.01)	-187.74	
Translog	(0, 0)	-194.10	12.71
Generalized Leontief	(.5, .5)	-190.03	4.57
Normalized Quadratic	(.5, 1)	-188.89	2.29
Square-rooted Quadratic	(1, 1)	-190.83	6.17

[a] Critical value of Likelihood Ratio Test = $-2(L(\delta^*,\lambda^*) - L(\delta,\lambda)) \sim \chi^2_{2,.05} = 5.99$, where δ^* and λ^* are the unrestricted power transformations.

but strongly rejecting the TL was consistent with the nonnested stochastic dominance test results of Shumway and Lim based on the same U.S. data. Using different data sets for U.S. agriculture, Gottret failed to reject all four functional forms for a restricted profit function, while Chalfant rejected all forms considered for a cost function. Chalfant did not nest the NQ in his QBCM tests. Varying test results have also been obtained by Appelbaum and by Berndt and Khaled using U.S. manufacturing data. They tested the TL, GL, and SRQ forms. Appelbaum rejected all three forms for a primal specification and failed to reject only the SRQ for a cost function specification. Berndt and Khaled failed to reject only the GL for their cost function.

Thus, prior results of nested and nonnested functional form tests on production data do not provide clear stylized facts against which to test our results. What does emerge from these earlier studies plus the current one are the following points: (1) the NQ has not been rejected in any of the four production applications where it has been tested, (b) lower but similar support is provided for the GL and SRQ, and (c) least support is provided for the TL. Exactly the same findings are obtained from either a comparison of order ranks of the test statistics or frequency of rejection of the alternative functional forms.

Predictive Accuracy

To examine predictive performance, the three most commonly-estimated locally-flexible functional forms (TL, GL, and NQ) were initially estimated with observations from 1951 to 1982. Observations from 1983 to 1986 were utilized to examine one-year-ahead out-of-sample predictive accuracy. The mean absolute percent error (MAPE), and the value share-weighted absolute percent error (VSWAPE) of predicting all output supplies were the two criteria used to evaluate each functional form's performance (Greene, p. 197). MAPE is mean absolute deviation expressed for ease of comparison in percent terms. VSWAPE combines the MAPEs for all outputs into a single measure of prediction error by weighting each MAPE by the output's share of total value of production. Table 3 presents the empirical predictive performance measures along with the 67 percent forecast confidence intervals (Greene, p. 195). The confidence intervals were computed assuming the forecast errors were normally distributed.

The forecast errors from all functional forms and all commodity groups were quite high. These large errors were due to the extremely poor 1983 forecasts when a major change occurred in government programs.

Considering MAPE values for each output supply, vegetable output was predicted best by the NQ while other crop and livestock outputs were predicted best by the GL. For vegetables, the TL performed very poorly. Thus, based on MAPE results, the NQ provided the best output predictive performance for the commodity group of primary concern. However, its performance was worst for the other crops supply equation. Because of the relative importance of the output category for which it was the worst predictor, it also ranked as the poorest predictor using the VSWAPE criterion. Considering only that criterion, the GL ranked as the best predictor.

Table 3. Mean Absolute Percent Error for Three Functional Forms

	Translog	Generalized Leontief	Normalized Quadratic
Commodity·			
Vegetables	83.6 (0, 176.1)	14.7 (0, 37.9)	10.6 (0, 31.5)
Other Crops	26.3 (11.8, 40.8)	25.0 (0, 56.7)	32.5 (0, 66.5)
Livestock	17.7 (0, 99.3)	17.4 (9.5, 25.3)	17.7 (10.1, 25.3)
Value Share-Weighted Absolute Percent Error	24.5 (0, 59.4)	22.7 (0, 48.0)	27.7 (.9, 54.5)

67 percent forecast confidence intervals are in parentheses.

Except for vegetables, the MAPE and VSWAPE from each functional form was within one standard deviation (i.e., the 67 percent forecast confidence interval) of other functional forms' forecast errors. Only the TL forecast for vegetables lay outside another functional form's confidence interval, namely both the GL and NQ's intervals.

Theoretical/Statistical Performance

Based on the conflicting relative performance of the NQ and GL in the Box-Cox tests and value share-weighted predictive accuracy comparison, both functional forms were examined further. The disaggregated systems of output supply and input demand equations, (7) and (8), were estimated, respectively, for the NQ and GL, maintaining linear homogeneity, symmetry, and convexity. The estimated parameters for the GL are presented in table 4. Parameters for the NQ are presented in table 5. Almost half of the NQ parameters were statistically significant at the .05 level. Fewer than 1/4 of the GL parameters were statistically significant. None of the price parameters were significant for the GL.

Convexity was tested for both functional forms using the approximation test of Talpaz et al. Computed F-statistics were .247 and .027 for the GL and NQ, respectively, with a critical value of $F^{.05}_{130,50} = 1.51$. Thus, convexity restrictions were not significantly violated by the unconstrained data with either functional form.

Monotonicity conditions for each functional form were checked at each observation by determining whether predicted netput levels were positive for outputs and negative for inputs. Both functional forms (NQ and GL) gave one violation early in the observation period which was statistically significant at the .05 significance level.

Tables 6 and 7 present elasticity estimates and their approximate standard errors for each functional form. Standard errors were computed based on a first-order Taylor-series expansion of the elasticities (Miller et al.). Results for the GL indicate that only two of its own-price elasticity estimates were statistically significant at the .05 level, while eight (including two own-price elasticities) were significant for the NQ. Absolute own-price elasticities ranged between .06 for materials and 2.08 for pesticides with the GL, and between .10 for materials and 1.33 for pesticides with the NQ. The largest and smallest elasticities in absolute values were 2.66 and .003 for the GL and 1.38 and .004 for the NQ. Major differences in own-price elasticities between the functional forms were estimated for several output and input categories. Estimated signs on 40 percent of the cross-price elasticities were sensitive to functional form.

There was no difference in the performance of these two functional forms based on theoretical expectations, but a larger share of the NQ parameter estimates was statistically significant. In terms of their empirical implications, important elasticity differences were found between the functional forms for several categories.

Conclusions

Functional form selection for dual model specifications can be perplexing. This paper has

Table 4. Parameter Estimates for the Generalized Leontief

Variable[a]	Parameter Estimate	Standard Error	Variable	Parameter Estimate	Standard Error
1/Veg P	.142485	.0808275	Fixed|Veg	-.0000371	.0000245
1/NS P	-.332208	.183668	Fixed|NS	.000176*	.0000505
1/Live P	-1.00291*	.490970	Fixed|Live	.0004351*	.0001375
1/Mat P	3.34976*	1.04466	Fixed|Mat	-.0011415*	.0002824
1/Pest P	.095576	.333326	Fixed|Pest	.0000104	.0001024
Veg Constant	-.0344872	.0484797	Rain|Veg	-.0000757	.0003096
NS P/Veg P	-.0265758	.0140864	Rain|NS	-.0016110*	.0006695
NS Constant	.0473929	.107024	Rain|Live	.0011451	.0018245
Live P/Veg P	.0139950	.0210999	Rain|Mat	.0017676	.0037094
Live P/NS P	-.0458378	.0558821	Rain|Pest	-.0000825	.0013133
Live Constant	-.0305255	.224179	Temp|Veg	.0004509	.0005578
Mat P/Veg P	.0110139	.0298543	Temp|NS	-.0006969	.0011844
Mat P/NS P	.0039723	.0746148	Temp|Live	.0022685	.0032730
Mat P/Live P	-.0872330	.180818	Temp|Mat	.0006836	.0067169
Mat Constant	-.0942110	.287018	Temp|Pest	-.0001505	.0023462
Pest P/Veg P	.0170980	.0235306	EDP|Veg	.0718368	.0451093
Pest P/NS P	-.0214241	.0553924	EDP|NS	-.209731*	.0982261
Pest P/Live P	.0071283	.102481	EDP|Live	-.209843	.276241
Pest P/Mat P	.0716850	.135687	EDP|Mat	.284675	.560254
Pest Constant	-.260950	.214366	EDP|Pest	-.0220962	.200598
GS|Veg	9.0000E-07	.0000014	Time|Veg	.0000692	.0010013
GS|NS	-.0000069*	.0000030	Time|NS	.0093819*	.0023151
GS|Live	.0000059	.0000084	Time|Live	.0311003*	.0053323
GS|Mat	.0000339	.0000173	Time|Mat	-.0560925*	.010259
GS|Pest	-.0000011	.0000061	Time|Pest	.0017575	.0048280

*Significant at .05 level.

[a] All price variables are raised to the .5 power. See equation (8). Price ratio variables are listed for the denominator's quantity equation; in the numerator's equation, the variables are inverted. Prices are normalized (divided) by the hired labor-capital price. The variable following | identifies the equation in which the variable appears.

Codes: P - price, Veg - vegetables, NS - other non-supported crops, Live - livestock, Mat - materials, Pest - pesticides, GS - government-supported crop output, Fixed - fixed input quantity, Rain - rainfall, Temp - temperature, EDP - effective diversion payment.

considered three selection criteria in choosing a functional form for model specification of Texas vegetable production. Box-Cox testing techniques were implemented to discriminate among commonly used functional forms belonging to the Box-Cox family. Results of this test suggested that the normalized quadratic and generalized Leontief were preferred in that order over the square-rooted quadratic and translog. Least support was given for the translog.

Out-of-sample predictive accuracy was examined for the translog, normalized quadratic, and generalized Leontief. Two measurement criteria were utilized to evaluate each functional form's performance. The normalized quadratic achieved the best mean absolute percent error in forecasting the vegetable output category, but the generalized Leontief achieved the best forecast error for the other output categories and the best value share-weighted percent forecast error for all categories.

Theoretical and statistical performance of the generalized Leontief and normalized quadratic was examined by estimating disaggregated systems of output supply and input demand equations while maintaining homogeneity, symmetry, and convexity conditions. No difference was found between the two functional forms in theoretical performance -- convexity was not rejected by either, and monotonicity was significantly violated at one early

Table 5. Parameter Estimates for the Normalized Quadratic

Variable[a]	Parameter Estimate	Standard Error	Variable	Parameter Estimate	Standard Error
Veg Constant	.120265*	.0524335	Fixed|Veg	-.0000239	.0000160
NS Constant	-.370374*	.178452	Fixed|NS	.0001600*	.0000550
Live Constant	-1.06318*	.372521	Fixed|Live	.0004199*	.0001120
Mat Constant	3.31721*	.790849	Fixed|Mat	-.0011613*	.0002332
Pest Constant	.0792743	.04077	Fixed|Pest	-.0000365*	.0000119
Veg P|Veg	.0133678*	.0056310	Rain|Veg	-.0000389	.0001995
NS P|Veg	-.0149712*	.0047712	Rain|NS	-.0016314*	.0007192
NS P|NS	.0199692	.0180623	Rain|Live	.0011674	.0014576
Live P|Veg	-.0039922	.0057725	Rain|Mat	.0020170	.0030528
Live P|NS	-.0085507	.0174575	Rain|Pest	.0002034	.0001491
Live P|Live	.0541546	.0367921	Temp|Veg	.0003472	.0003555
Mat P|Veg	-.0040723	.0102116	Temp|NS	-.0007154	.0012734
Mat P|NS	.0185499	.0303025	Temp|Live	.0023445	.0026405
Mat P|Live	-.0556765	.0562917	Temp|Mat	-.0000074	.0055262
Mat P|Mat	.0627603	.136585	Temp|Pest	-.0005913*	.0002652
Pest P|Veg	.0025141	.0035747	EDP|Veg	.0769415*	.0282169
Pest P|NS	-.0003260	.0037447	EDP|NS	-.210441*	.102441
Pest P|Live	-.0108784*	.0047270	EDP|Live	-.217984	.215475
Pest P|Mat	.0131372	.0074951	EDP|Mat	.311993	.453383
Pest P|Pest	.0273112*	.0053280	EDP|Pest	.0227383	.0209747
GS|Veg	3.0000E-07	9.3817E-07	Time|Veg	-.0002400	.0005321
GS|NS	-.0000061	.0000033	Time|NS	.0098191*	.0017954
GS|Live	.0000055	.0000067	Time|Live	.0300619*	.0037512
GS|Mat	-.0000325*	.0000142	Time|Mat	-.0572113*	.0079535
GS|Pest	.0000027*	7.6319E-07	Time|Pest	-.0022351*	.0004404

* Significant at .05 level.

[a] The variable following | identifies the equation in which the variable appears; by symmetry the price of the variable to the right of | also appears in the quantity equation of the variable to the left (for Veg, NS, Live, Mat, and Pest) and has the same parameter estimate. Prices are normalized by the hired labor-capital price. See equation (7). For codes, see table 4.

observation by both. Nearly twice as many of the normalized quadratic parameter estimates as generalized Leontief parameter estimates were statistically significant.

Considering the three criteria of nested hypothesis testing, predictive performance, and statistical fit, the normalized quadratic functional form appears to be marginally preferred for this data set. Further, both the normalized quadratic and generalized Leontief were preferred over the translog. These findings were consistent with a plurality of somewhat ambiguous prior evidence on functional form choice for production analysis.

While the final results of this study are somewhat ambiguous, the strength of the approach taken here is that the problem has been examined from several different perspectives. Had we only conducted the nested Box-Cox hypothesis tests, we would have clearly chosen the normalized quadratic on the basis of likelihood support. Although it may seem a negative conclusion, the benefit of including the other tests in this case was to caution the analyst about assigning too strong a preference to any one alternative.

Table 6. Elasticity Estimates for the Generalized Leontief

	Elasticity with Respect to the Price of					
Output or Input	Vegetables	Non-Supported Crops	Livestock	Materials	Pesticides	Hired Labor-Capital
Vegetables	.094 (.484)	-.225 (.238)	.110 (.333)	.070 (.381)	.137 (.378)	-.188 (.175)
Non-Supported Crops	-.062 (.066)	.168 (.848)	-.169 (.413)	.012 (.446)	-.081 (.417)	.132 (.222)
Livestock	.006 (.019)	-.035 (.085)	.101 (.318)	-.050 (.208)	.005 (.148)	-.027 (.064)
Materials	-.005 (.028)	-.003 (.120)	.065 (.271)	-.057 (.349)	-.055 (.208)	.055 (.143)
Pesticides	-.118 (.326)	.251 (1.298)	-.078 (2.240)	-.635 (2.404)	-2.077 (4.777)	2.657* (.264)
Hired Labor-Capital	.021 (.019)	-.053 (.089)	.054 (.126)	.083 (.215)	.343* (.029)	-.447 (.267)

Approximate standard errors are in parentheses.

*Significant at .05 level.

Table 7. Elasticity Estimates for the Normalized Quadratic

	Elasticity with Respect to the Price of					
Output or Input	Vegetables	Non-Supported Crops	Livestock	Materials	Pesticides	Hired Labor-Capital
Vegetables	.189* (.081)	-.359* (.117)	-.089 (.129)	-.074 (.185)	.057 (.082)	.276 (.250)
Non-Supported Crops	-.114* (.040)	.258 (.237)	-.103 (.211)	.181 (.298)	-.004 (.046)	-.218 (.363)
Livestock	-.005 (.007)	-.018 (.036)	.105 (.071)	-.087 (.088)	-.021* (.009)	.027 (.088)
Materials	.005 (.013)	-.039 (.063)	.108 (.110)	-.099 (.215)	-.026 (.015)	.050 (.186)
Pesticides	-.076 (.108)	.017 (.192)	.519* (.233)	-.508 (.295)	-1.327* (.299)	1.375* (.516)
Hired Labor-Capital	-.022 (.020)	.054 (.089)	-.038 (.126)	.058 (.215)	.081* (.029)	-.133 (.267)

Approximate standard errors are in parentheses.

*Significant at .05 level.

References

Appelbaum, E. "On the Choice of Functional Forms." *Intern. Econ. Rev.* 20(1979):449-57.

Baffes, J., and U. Vasavada. "On the Choice of Functional Forms in Agricultural Production Analysis." *Appl. Econ.* 21(1989):1053-61.

Ball, V. E. "Modeling Supply Response in a Multiproduct Framework." *Amer. J. Agr. Econ.* 70(1988):813-25.

Berndt, E. R., and M. S. Khaled. "Parametric Productivity Measurement and Choice among Flexible Functional Forms." *J. Polit. Econ.* 87 (1979):1221-45.

Chalfant, J. A. "Choosing among Flexible Functional Forms: An Application of the Generalized Box-Cox and the Fourier Flexible Functional Forms in U.S. Agriculture." Ph.D. thesis, North Carolina State University, 1983.

Dutta, J. "On Predictive Evaluation of Econometric Models." *Intern. Econ. Rev.* 21(1980):379-89.

Gottret, P. E. "A Regional Approach to the Estimation of Multiproduct Input Demand and Output Supply Functions in the U.S." Ph.D. thesis, Texas A&M University, 1987.

Greene, W. H. *Econometric Analysis.* New York: Macmillan Publishing Co., Second Edition, 1993.

Griffin, R. C., J.M. Montgomery, and M. E. Rister. "Selecting Functional Form." *West. J. Agr. Econ.* 18(1987):216-27.

Guilkey, D. K., C. A. K. Lovell, and R. C. Sickles. "A Comparison of the Performance of Three Flexible Functional Forms." *Intern. Econ. Rev.* 24(1983):591-615.

Houck, J.P., and M.E. Ryan. "Supply Elasticities of Corn in the United States: The Impact of Changing Government Programs." *Amer. J. Agr. Econ.* 54(1972):878-92.

Huffman, E. W., and R. Evenson. "Research Bias Effects for Input and Output Decisions: An Application to U.S. Cash-Grain Farms." *Amer. J. Agr. Econ.* 71(1989):761-73.

Jorgenson, D. W., and L. J. Lau. "The Structure of Consumer Preferences." *Ann. Econ. and Soc. Meas.* 4(1975):49-101.

Lau, L. J. "Testing and Imposing Monotonicity, Convexity, and Quasi- Convexity Constraints." pp. 409-53 in *Production Economics: A Dual Approach to Theory and Applications* (eds., M. Fuss and D. McFadden), Volume 1, Amsterdam: North-Holland, 1978.

Lim, H., "Profit Maximization, Returns to Scale, Separability, and Measurement Error in State-Level Agricultural Technology." Ph.D. Thesis, Texas A&M University, 1989.

Lim, H. and C.R. Shumway. "Separability in State-Level Agricultural Technology." *Amer. J. Agr. Econ.* 74(1992):120- 31.

Lopez, E. R. "Estimating Substitution and Expansion Effects Using a Profit Function Framework." *Amer. J. Agr. Econ.* 66(1984):358-67.

McIntosh, C.S. "Evaluating Alternative Methods of Including Government Policy Information for Multiproduct Supply Analysis." Working Paper, University of Georgia, 1990.

_________. "Specification of Government Policy Variables." Division of Agricultural Economics FS89-61, University of Georgia, 1989.

Miller, S. E., O. Capps, and G. J. Wells. "Confidence Intervals for Elasticities and Flexibilities from Linear Equations." *Amer. J. Agr. Econ.* 66(1984):392-96.

Moschini, Giancarlo. "A Model with Supply Management for the Canadian Agricultural Sector." *Amer. J. Agr. Econ.* 70 (1988):318-29.

Ornelas, F. S., C.R. Shumway, and T. Ozuna. "Functional Form Selection and Dual Profit Functions for U.S. Agriculture." Paper presented at the Southern Agricultural Economics Association annual meetings, Fort Worth, Texas, February, 1991.

Romain, R.F.J. "A Commodity Specific Policy Simulation Model for U.S. Agriculture." Ph.D. thesis, Texas A&M University, 1983.

Shumway, C. R., and W.P. Alexander. "Agricultural Product Supplies and Input Demands: Regional Comparisons." *Amer. J. Agr. Econ.* 65(1988):153-61.

Shumway, C. R., and H. Lim. "Functional Form and U.S. Agricultural Production Elasticities." *J. Agr. and Res. Econ.* 18(1993):forthcoming.

Swamy, G., and H. Binswanger. "Flexible Consumer Demand Systems and Linear Estimation: Food in India." *Amer. J. Agr. Econ.* 65(1983):675-84.

Talpaz, H., W.P. Alexander, and C.R. Shumway. "Estimation of Systems of Equations Subject to Curvature Constraints." *J. Stat. Comp. and Simul.* 32(1989):201-16.

Teigen, L. D., and F. Singer. "Weather in U.S. Agriculture: Monthly Temperature and Precipitation by State and State Farm Production Region, 1950-1986." USDA, Economic Research Service Statistical Bulletin No. 765, Washington, 1988.

Texas Department of Agriculture. *Texas Vegetable Statistics*, Austin, various issues.

Thompson, D. G. "Choice of Flexible Functional Form and Appraisal." *W. J. Agr. Econ.* 13(1988):169-83.

United States Department of Agriculture. *Agricultural Statistics*, Washington, various issues.

Villezca, P. A. "Functional Form, Model Specification, and Analytical Simplification in Multiple-Output Production Analysis." Ph.D. thesis, Texas A&M University, 1991.

Endnotes

1. Aggregate data were used for the Box-Cox estimation because of the potential for convergence problems when estimating parameters associated with the less aggregated data used in the subsequent comparisons.

2. Using nonparametric tests, Lim failed to reject the profit-maximization hypothesis for Texas agricultural production. While there were some observed violations of the joint hypothesis of profit maximization, convex technology, and nonregressive technical change, Lim found that the violations were trivial. Measurement errors in the quantity data averaging 1.1 percent could have accounted for all violations.

3. Lim compared four specifications of commodity price expectations (lagged price, futures, ARIMA forecast, and composite) in two states (Texas and Iowa). In both states he found that lagged prices gave the lowest estimates of measurement error required for consistency with the joint hypothesis of profit maximization, convex technology, and nonregressive technical change.

4. For ease in implementing the first procedure for functional form evaluation, the Box-Cox profit function (1) was estimated without appending the system of first-derivative equations. Because of high collinearity, the profit function was not estimated as part of the system of supply/demand (or share) equations in (7) or (8) for the latter two evaluative procedures. Both approaches provide consistent estimates but with some loss of efficiency because one or more relevant equations were omitted in each model. Thus, they provide conservative estimates of standard errors (upper bound) and likelihood ratio test statistics (lower bound).

5. Iterative SUR produces maximum likelihood (ML) estimates for all model parameters, including those in the variance-covariance matrix. Therefore, this stabilized cross-equation covariance matrix was ML for the system of equations which maintained homogeneity and symmetry.