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ENDOGENOUS REGIONAL AGRICULTURAL PRODUCTION TECHNOLOGIES

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ABSTRACT

This research examines and compares estimates of technical bias for each of ten multistate farm production regions comprising the contiguous 48 states of the United States. The applied methodology allows for price-dependent aggregate technical choice and stochastic variation of the production technology in computing measures of technical bias.

ENDOGENOUS REGIONAL AGRICULTURAL PRODUCTION TECHNOLOGIES

1. INTRODUCTION

Recent contributions to production economics which focus on specifying models that capture information about the underlying structure of technology have garnished considerable exposure in the literature. Dual and primal specifications of production systems, such as those by McKay et al. (1983), Just et al. (1983), and Livernois and Ryan (1989) are the most common. Perhaps the two most striking methodological departures from conventional primal and dual modeling constructs have been the application of nonparametric analysis and the development of frontier technology models. While the foundation of nonparametric production analysis was developed nearly 20 years ago by Hanoch and Rothschild (1972) and Afriat (1972), work in the early 1980s by Diewert and Parkan (1983) and Varian (1984) induced a resurgence of interest and several empirical applications. Nonparametric methodologies have provided insight into the consistency of observed data vectors with conventional maintained hypotheses invoked in classical empirical analysis. While this information has great utility in developing models of technology, its usefulness is restricted by the limited inferencing mechanism available for investigating the significance of departures from maintained hypotheses (Varian, 1985).

Frontier technology models, on the other hand, claim an origin in Farrell's (1957) work and are designed to assess technical, allocative, and scale inefficiencies. In contrast to nonparametric methods, some frontier technology models do provide formal inferencing mechanisms to investigate apparent production inefficiencies, e.g., Meeusen and van den Broeck (1977) and Kumbhakar (1988). However, while the frontier approach to model development has great utility in investigating micro-level data, its interpretation in an aggregate model may beg the question of technical inefficiency. For aggregate models in which microproduction processes are aggregated across segmented intraregional market structures, it is conceivable that behavior which appears to be inefficient may actually be associated with market dependent, systematic movement of the aggregate unit isoquant over some range of the technology map. We are unable to isolate perturbations in market structure from endogenous choice of microproduction processes and techniques. This fact necessitates the development of a model which provides the flexibility to adapt to aggregate technologies and yet provides information on the nature of technical choice under both systematic and stochastic variation in the frontier.

Mundlak (1988) has presented a theoretical framework for price-dependent aggregate technical choice from available microproduction processes. Fawson et al. (1990) have provided a methodology to empirically implement the Mundlak framework. Utilizing a generalized Fechner-Thurstone (GFT) functional form and assuming that producers can compute optimal solutions to known nonstochastic production technologies (or hire people who can), their parametric specification permits optimization errors associated with changing technology to occur because of (a) stochastic variation of the production technology map, (b) alterations of the microproduction functions, and/or (c) choice among available microproduction techniques.

Analyses of aggregate production most often treat the technology as known and, except for possibly being time dependent, exogenous. Random error terms are generally tacked on to estimation equations and regarded as errors in optimization of a known technology rather than knowledge errors about the technology. In agriculture, the production period is particularly long and output is subject to the vagaries of highly uncertain and unpredictable weather. Thus, a major source of production variation is weather-induced changes in the technology map itself. In addition, microproduction processes and techniques change rapidly, and the aggregate technology is dependent upon firm-level choices from among the available set of microproduction processes. Changes in economic variables may provide incentive for producers to alter their choice of specific production techniques and microproduction processes.

The objective of this study is to examine endogenous technical choice in each of ten multistate farm production regions comprising the contiguous 48 states of the United States. The GFT production system will be employed to examine annual time series data for the period 1950-1982. The econometric model is presented in the following section. Results of the empirical application are contained in Section 3. The results are summarized in Section 4.

2. *THE ECONOMETRIC MODEL*

The aggregate production system for each geographic production region is modeled in a manner consistent with profit-maximizing price-taking behavior subject to a budget constraint. Under conditions of a single aggregate output index, budget-constrained output maximization yields the same optimal solution as budget-constrained profit maximization. Let P be a vector of factor prices and let C denote expenditure on factors in a specified production period which is effectively constrained at C*. It is assumed that producers select a definite equilibrium n-tuple production bundle $X = (x_1, ..., x_n)$ such that the choice results in maximization of a GFT production function for aggregate output:

$$(1) \qquad F(X;\theta) = a\Pi_i x_i^{\theta_i(\gamma)}.$$

subject to

$$(2) \qquad C = \Sigma_i p_i x_i,$$

where the n-tuple θ of positive-valued functions, $\theta_i(\gamma)$ i = 1,..., n, is the parameter vector of $F(X;\theta)$. For constant γ, the GFT production function is homogeneous of degree $\Sigma_i\theta_i$, strongly separable and homothetic in X, and exhibits constant elasticity of substitution among elements of X equal to unity everywhere.

In terms of economic behavior, elements of the argument vector X are under the producer's control whereas elements of the parameter vector $\theta(\gamma)$ are not. The components of γ are referred to as technology changers. These are classified as: (a) technology changers that are systematic and observable, and (b) technology changers that are stochastic and nonobservable. It is assumed that the marginal products derived from $F(X;\theta)$ can be expressed as a product of a systematic function and a stochastic element.

We have chosen to assess two subclasses of the whole GFT-class: the constant elasticity of marginal rate of technical substitution form (GFT-CEMRTS), and the constant ratio of elasticity of substi-tution form (GFT-CRES). Neither functional form subclass (hereafter referred to as a class) imposes restrictions on comparative statics at a point. Thus, both are locally flexible representations of the aggregate production function in the technology changer variables. Because no likelihood support was found by Fawson et al. (1990) for alternative restricted functional forms nested within each of these classes, only the results of these two general classes will be examined in this paper.

GFT-CEMRTS Form

The GFT-CEMRTS form specifies that the $\theta(\gamma)$ parameters of (1) are characterized as follows:

$$(3) \qquad \theta_i^*(C,P,Z) = \beta_i C^{w_{io}} \Pi_j p_j^{w_{ij}} \Pi_q z_q^{w_{iq}}, \; i,j = 1,..., n; \; q = 1,..., m,$$

$$(4) \qquad \theta_i = \theta_i^* e^{u_i}, \quad i = 1,..., n,$$

where $u = \{u_1, ..., u_n\}$ is a latent random vector with a mean of zero and a finite positive definite variance matrix, Ω_o. The vector u characterizes a vector of stochastic technology changers. In addition, the serial covariance matrices Ω_s, s = 1, 2, ..., n, may represent persistence of effects of stochastic changes in technology. The vector

Z characterizes systematic technology changers which are not parameters of the expenditure constraint and may include demographic information, weather variables, lagged values of C and P, and other exogenous variables.

Taking logarithms of the ratio of Θ_i to Θ_k yields the n-1 estimation equations for the GFT-CEMRTS model:

$$\ln(S_i/S_k) = \ln(\beta_i/\beta_k) + w^k_{io}\ln(C) + \Sigma_j w^k_{ij}\ln(p_j) + \Sigma_q w^k_{iq}\ln(z_q) + \epsilon^k_i, \tag{5}$$

$$i = 1, ..., n, i \neq k,$$

where $w^k_{io} = w_{io} - w_{ko}$, $w^k_{ij} = w_{ij} - w_{kj}$, $w^k_{iq} = w_{iq} - w_{kq}$, and $\epsilon^k_i = u_i - u_k$.

GFT-CRES Form

The $\Theta(\gamma)$ parameters of (1) for the GFT-CRES form are characterized as follows:

$$\Theta^*_i\,(C,P,Z) = \beta_i\Pi_j[x^*_j(C,P,Z)]^{b_{ij}}\,\Pi_q z_q^{b_{iq}}\ ,\ i,j = 1, ..., n;\ q = 1, ..., m, \tag{6}$$

$$\Theta_i = \Theta^*_i e^{u_i}\ . \tag{7}$$

In equilibrium, $x_j = x^*_j(C, P, Z)$, $j = 1, ..., n$, which are unknown functions. Since Θ^*_j is functionally dependent only on (C, P, Z) when the first-order conditions are satisfied, taking logarithms of the ratio of Θ_i to Θ_k yields the n-1 estimation equations for the GFT-CRES model:

$$\ln(S_i/S_k) = \ln(\beta_i/\beta_k) + \Sigma_j b^k_{ij}\ln(x_j) + \Sigma_q b^k_{iq}\ln(z_q) + \epsilon^k_i\,, \tag{8}$$

$$i = 1, ..., n, i \neq k\,,$$

where $b^k_{ij} = b_{ij} - b_{kj}$, $b^k_{iq} = b_{iq} - b_{kq}$, and $\epsilon^k_i = u_i - u_k$.

Estimation

The stochastic variables, u_i, are explicitly included in the specification of the parameter vector and are not simply tacked on to the estimation equations. These error terms are assumed to be due to stochastic changes in the aggregate technology not collectively anticipated by decision makers rather than to errors in optimizing behavior. Nevertheless, the estimated equations obviously are not perfect fits of the actual optimizing behavior due to the presence of unobserved causal variables which change over the data period and to measurement errors on observed variables.

The random element ϵ^k_i in each estimation equation (5) and (8) is assumed to follow a second-order autoregressive schema:

$$\epsilon^{k}_{i,t+2} - \Phi_{i,1}\epsilon^{k}_{i,t+1} + \Phi_{i,2}\epsilon^{k}_{i,t} = \epsilon_{i,t+2}, \forall i,k, \tag{9}$$

where $E[\epsilon_t] = 0$, $E[\epsilon_t\epsilon_s] = 0$ for $t \neq s$, and $E[\epsilon_t^2] = \sigma_\epsilon^2$.

Following Basmann (1985), the autocovariance matrices are determined by the variance matrix and the two AR(2) autocorrelation coefficients, $\Phi_{i,1}$ and $\Phi_{i,2}$. Minimal sufficient statistics for each empirical model are estimated using the general linear model (GLM). The dependent variable vector and the matrix of independent variables are transformed according to a maintained AR(2) hypothesis on $\Phi_{i,1}$ and $\Phi_{i,2}$ values over the stability domain implied by the Routhian conditions (Kenkle, 1974). The GLS estimators are then obtained by applying the method of least squares to the transformed model.

3. EMPIRICAL APPLICATION

The data used in this analysis were constructed by Fawson and Gottret (1988) and represent a comprehensive divisia index characterization of both prices and quantities of production aggregates for each of ten USDA specified farm production regions from 1950 to 1982. Variables include prices (P) and quantities (X) of six variable factors: hired labor, machinery, energy, fertilizer and pesticides (chemicals), marketing and processing services for feed, seed, and livestock (FSL), and other materials. They also include total expenditure on these variable factors (C) and seven additional systematic technology changers (Z): year, real estate quantity, family labor quantity, sample standard deviation of monthly average temperatures over the year, sample mean of monthly average temperatures for the year, sample standard deviation of monthly precipitation over the year, and sample mean of monthly precipitation for the year. Using these data, a five-equation system, (5) or (8), is estimated for each GFT-class model with materials designated as the numeraire factor. With a single output index and a binding budget constraint, the optimal solution is not dependent on output price. Thus, output price does not appear as one of the exogenous price variables in the estimation equations.

The first stage of the empirical application utilized a grid search method to assess likelihood support for alternative serial correlation hypotheses on the stochastic technology changers. Hicksian technical bias is then investigated, conditional on maintained AR(2) specifications which generated the highest likelihood support, by computing primal cost-share-weighted summary measures of the sensitivity of marginal rates of technical substitution to changes in the technology changer variables.

Specification of the Autoregressive Process

The likelihood support for alternative autocorrelation parameters $\Phi_{i,1}$ and $\Phi_{i,2}$ was examined by means of a grid search of 138 two-tuple sets of autocorrelation parameters specified to provide extensive coverage within the stability triangle of a second-order autoregressive schema. The likelihood support for a given AR(2) hypothesis within a model class was assessed by examining the ratio of the likelihood function for a specific AR(2) two-tuple hypothesis set relative to the maximum value of the likelihood function over all 138 AR(2) hypothesis sets in the stability region. Three-dimensional plots of likelihood support were prepared for each model class in each production region. They revealed that several of the regional processes do not exhibit singly peaked likelihood grids. Almost half of the production regions for each class have saddle points in the Φ_1 plane. In addition, the plots for several production regions are highly skewed and not all in the same direction. Although both the autocorrelation parameters with maximum likelihood support and the shape of the likelihood support surface varied greatly across regions, examination of the three dimensional plots reveal little likelihood support for the hypothesis of zero serial correlation. In fact, in no region was the likelihood support for the hypothesis of zero serial correlation within 40 percent of the maximum value of the likelihood function.

Calculation of Technical Bias

Following the convention of Lau (1978) and others, we define direct Hicks-neutral technical change as expansion-path-preserving technical change. A direct Hicksian measure of technical bias then would assess the sensitivity of marginal rates of technical substitution at a given point in input space to changes in technology changing instruments. Because our GFT conceptualization treats the aggregate production technology map as endogenous in every period, each variable regarded as exogenous for a particular GFT class becomes a potential source of technical bias. Estimated parameters in (5) and (8) are the elasticities of the marginal rates of technical substitution with respect to exogenous variables for the respective GFT-class models. Thus, they are straightforward primal-based measures of direct Hicksian bias. Following Antle (1988, p. 357) and Antle and Capalbo (1988, pp. 38-39), primal cost-share-weighted summary measures of Hicksian bias for input i with respect to technology changer h were computed at given input levels as:

(10) $$B_{i,h}(X, \gamma_h) = \Sigma_j S_j \, \partial \ln(f_i/f_j)/\partial \ln\gamma_h,$$

where S_i is the i^{th} input's cost share, f_i is $\partial \ln F/\partial \ln x_i = \Theta_i$, and γ_h is the h^{th} exogenous variable. For the GFT-CEMRTS class,

(11) $$B_{i,h}(X, \gamma_h) = \Sigma_j S_j w^j_{ih} = \Sigma_j S_j(w^k_{ih} - w^k_{jh}),$$

where k is the numeraire factor. For the GFT-CRES class,

(12) $$B_{i,h}(X, \gamma_h) = \Sigma_j S_j(b^k_{ih} - b^k_{jh}).$$

Equation (10) is qualitatively identical to Antle's (1988) and Antle and Capalbo's (1988) primal summary measures of Hicksian bias. For example, when technology changer γ_h is the trend variable, technical change is Hicks neutral, using, or saving with respect to time as $B_{i,h} = 0$, $B_{i,h} > 0$, or $B_{i,h} < 0$, respectively. In general, the i^{th} factor's relative marginal product is on average directly (inversely) related to variation in technology changer γ_h as $B_{i,h} > 0$ ($B_{i,h} < 0$). Summary measures of bias were computed at the data means for the GFT-CEMRTS and GFT-CRES model class and each production region.

Evidence for the classical interpretation of factor using and saving technical changes (i.e., with respect to time) suggests that the factors machinery and chemicals have been predominantly and significantly (.05 level) factor using across regions and model classes while feed-seed-livestock marketing and processing services (FSL) has been predominantly and significantly factor-saving across regions and model classes. The preponderance of significant evidence on fixed factors and weather variables as technology changer variables, which are common to both models, suggest the following:

a. Increases in the real estate factor have had a positive impact on the relative marginal product of energy and a negative impact on the relative marginal product of hired labor, chemicals, and FSL.

b. Increases in the family labor factor have had a positive impact on the relative marginal product of hired labor and chemicals and a negative impact on the relative marginal product of energy.

c. Increases in the standard deviation of temperature have had a positive impact on the relative marginal product of machinery and a negative impact on the relative marginal product of energy and chemicals.

d. Increases in the mean temperature have had a negative impact on the relative marginal product of energy.

e. Increases in the mean precipitation have had a negative impact on the relative marginal product of energy and chemicals.

Overall, energy and chemicals appear to have been the most consistently affected by changes in technology changer variables common to both models.

For factor price and total cost technology changer variables, which are endemic only to the GFT-CEMRTS class model, technical change bias measures suggest that the following variables exhibited a significant and generally consistent impact on relative marginal factor productivity in more than half of the regions. Hired labor was factor using and chemicals were factor saving in the price of hired labor. Machinery and hired labor were factor using and FSL and materials were factor saving in the price of machinery. Machinery was factor using in the price of energy. Chemicals, machinery, and energy were factor using and FSL was factor saving in the price of chemicals. FSL was factor using and chemicals was factor saving in the price of feed-seed-livestock marketing and processing services. Chemicals were factor using and materials were factor saving in the total cost of variable factors.

For the GFT-CRES class model, economic variables influence the technology map through the functions $x_j^*(C, P, Z)$ which are unknown. As a result, the influence of economic variables on the production technology map is observed only through factor utilization, and we are unable to distinguish between price and budget effects. Therefore, the Hicksian summary bias measures for these factor utilization variables lack a clear intuitive meaning.

For variable relationships other than those identified above, a great deal of variability across regions was evident among significant summary bias measures. For all possible pairs of regions with a significant summary bias measure for the same variable relationships, nearly a third had different signs. The large number of differences suggests that the aggregate agricultural technology differs in important ways among regions of the United States. Interregional differences in signs of the significant summary measures were substantially greater for the weather variables than for the temporal and fixed factor variables.

A great deal of variability among significant summary bias measures was also evident among model classes. A little over a third differed in sign between the GFT-CEMRTS and GFT-CRES models. Like the regions, differences among models were considerably greater for weather variables than for temporal and fixed factor variables.

The likelihood support plots, parameter estimates for each regional model evaluated at its respective maximum AR(2) hypothesis, detailed test statistics, and measures of Hicksian bias underlying the reported results are available upon request from the authors.

4. CONCLUSIONS

This research has examined endogenous technical choice as it relates to specification of aggregate regional agricultural production functions. The generalized Fechner-Thurstone (GFT) functional specification was employed to relax strict neoclassical efficiency constraints and to provide a means for modeling systematic and stochastic technical change without exclusive reliance on time trend variables as the only basis for shifts in the aggregate production technology map.

Two GFT-class models were specified under a second-order autoregressive schema: the constant elasticity of marginal rate of technical substitution model (GFT-CEMRTS) and the constant ratio of elasticity of substitution model (GFT-CRES). Summary measures of Hicksian bias suggested that changes in time and several other variables exhibit a significant systematic effect on the shape of regional agricultural production technology maps. This lends strong support to the hypothesis that aggregate models which ignore the systematic effect of nontemporal technology changer variables on technical choice have omitted an important tool for investigating the nature of aggregate production technologies.

Considerable evidence of substantial interregional differences in the aggregate agricultural technology maps was also observed. The autocorrelation parameters with maximum likelihood support and the shape of the likelihood surface varied greatly across regions. So did the signs of significant summary Hicksian bias measures. These findings lend further support to the notion that the aggregate agricultural technology differs in important ways among regions of the United States. Consequently, changes in the economic environment and/or government policies can be expected to impact the regions in fundamentally different ways.

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